Asia Pacific Science Press

Journal of Advances in Engineering and Technology
ISSN(O):3005-7507
ISSN(P):3005-7493
Vol. 3 No.2 (2026)

From Data Possession to Operations Reconfiguration: Transforming Firm Operations under Big Data - An Integrative Literature Review

Mengfei Xiao, Weixiang Gan*

Lincoln University College, Petaling Jaya, Selangor Darul Ehsan-47301, Malaysia

Corresponding author: Weixiang Gan, Gabriel1995@qq.com

Abstract: This integrative review develops a theory-oriented account of how big data transforms firm operations. Instead of treating big data analytics capability as a direct antecedent of firm performance, it examines how data is institutionalised, translated into decision routines, embedded in workflows, and orchestrated through platforms and ecosystems. Drawing on recent literature published mainly between 2017 and 2026 across management, information systems, operations, supply-chain, governance, and data-platform research, the review shows that operational transformation is not produced by analytics investment alone. Value emerges when firms combine data governance, privacy control, data quality, analytical culture, decision-right redesign, process instrumentation, automation, supply-chain integration, and platformised data architectures. The paper proposes a Data-to-Operations Reconfiguration Framework in which process visibility, decision-latency compression, exception detectability, and cross-boundary coordination explain how data becomes operational value. By moving beyond the conventional capability–performance view, this review positions big data as a socio-technical and institutional mechanism that reconstructs the operating model of the firm. It further identifies propositions around governance-mediated value creation, curvilinear centralisation effects, platform-enabled SME value capture, and resilience-oriented performance under environmental dynamism.

Keywords: Firm Operations; Operating Model; Big Data Analytics; Data Governance; Data-Driven Decision Making; Process Transformation; Supply-Chain Analytics; SMEs; Data Platforms

Published: May 24, 2026

DOI: https://doi.org/10.62177/jaet.v3i2.1384

1. Introduction

Big data has moved from a specialist information-technology issue to a structural condition of contemporary firm operations. Firms no longer rely only on transactional systems, enterprise resource planning modules and periodic managerial reports. They receive continuous signals from digital platforms, connected products, sensors, customer interfaces, logistics partners, payment systems, service channels and external data markets. This shift alters the grammar of operations. Traditional operating models were often organised around stable process designs, periodic reporting cycles, functional accountability and managerial judgement. Data-intensive operations make inventory, production, procurement, service encounters, demand fluctuations, supplier risks, quality deviations and customer complaints observable at a much finer temporal and spatial granularity. The managerial problem is no longer whether firms possess more data. It is whether data can be converted into an operating model that is more visible, faster, more adaptive and more accountable than the model it replaces.

The existing literature has established that big data analytics capability is associated with firm performance, innovation, decision quality and supply-chain improvement (Ansari & Ghasemaghaei, 2023; Mikalef et al., 2019; Oesterreich et al., 2022). This evidence is valuable because it demonstrates that analytics is not merely a technical investment. Yet the dominant causal vocabulary remains narrow. Many studies imply that firms acquire data resources, build analytical capability and then achieve superior performance. This formulation compresses the organisational transformation into a single causal arrow. A firm may have large data stores, modern cloud tools and data scientists while still making slow decisions, duplicating data across functions, confining insights to specialist teams or failing to embed predictive outputs into frontline work. Analytics adoption is not the same as operations transformation. The latter requires the redesign of governance arrangements, decision rights, process controls, data architectures and inter-organisational coordination mechanisms.

This distinction matters because recent research shows that performance effects depend on social, organisational and contextual conditions. Meta-analytic evidence suggests that technical factors alone do not explain the business value of analytics; social factors, culture and organisational routines shape value realisation (Oesterreich et al., 2022). Research on data-driven decision making shows that top management support, perceived data quality, analytical culture and centralisation in data use reshape the structure of decision routines rather than simply increasing the amount of information available to managers (Szukits & Móricz, 2024). Data governance and enterprise data marketplace research further indicates that data use depends on rules, metadata, quality assurance, access mechanisms and trust in data sharing (Abraham et al., 2023; Eichler et al., 2023; Nadal et al., 2022). Evidence from SMEs also shows that smaller firms often capture value through platform dashboards, ecosystem access and network capability rather than through a scaled-down version of the large-firm analytics stack (Bar-Gill et al., 2024; Bhatti et al., 2025).

This paper therefore reviews big data as a mechanism of operating-model reconfiguration. It synthesises literature on data governance, privacy, decision-making, process redesign, automation, supply-chain operations, performance realisation, data platforms and SME heterogeneity. The argument is that big data reshapes firm operations through three linked translations. Data must first be institutionalised through governance, privacy, quality, access and architecture. It must then enter decision-system redesign through analytical culture, decision-right redistribution, evidence-based escalation and accountability. It must finally be embedded into workflows through instrumentation, automation, supply-chain integration and platform orchestration. When these translations occur, big data creates operational value through four mechanisms: process visibility, decision-latency compression, exception detectability and cross-boundary coordination.

The contribution of the review is threefold. First, it reframes big data transformation as a multi-level operating-model problem rather than a generic technology-performance relationship. Second, it proposes a Data-to-Operations Reconfiguration Framework that integrates governance, decision redesign, operational embedding, mechanisms and boundary conditions. Third, it develops a research agenda around issues that remain under-theorised: governance-mediated operational value, curvilinear effects of centralisation, platform-based substitution for SME capability constraints and resilience-oriented value creation under environmental dynamism. The review is designed as a theory-building synthesis rather than a descriptive catalogue of digital technologies.

2. Review Approach and Scope

This study adopts a protocol-informed integrative literature review. It does not aim to estimate a pooled effect size or to cover every publication using the phrase big data. Its purpose is to synthesise high-relevance evidence across neighbouring fields that are often reviewed separately: information systems, strategic management, operations management, supply-chain management, data governance, data engineering, platform studies and SME digitalisation. This approach is appropriate because the transformation of firm operations under big data cannot be captured through one disciplinary lens. Governance research explains data access, quality, privacy and trust. Decision-making research explains how analytical evidence changes managerial authority and accountability. Operations and supply-chain research explains forecasting, visibility, integration and responsiveness. Architecture research explains how data lakes, lakehouses, marketplaces and data products affect the cost, timeliness and usability of analytics. SME research shows how resource constraints and platform dependence alter the path of value realisation.

The review concentrates on studies published between 2017 and 2026, with stronger emphasis on research published from 2021 onward. Earlier studies are retained only where they provide concepts still necessary for interpreting recent evidence, including the strategic business value framework of Grover et al. (2018), Vial's (2019) review of digital transformation, the econometric analysis of BDA and firm performance by Mueller et al. (2018) and the service-innovation analysis by Lehrer et al. (2018). The principal search channels informing the review are Web of Science, Scopus, Google Scholar, IEEE Xplore and ProQuest. Search terms combined concepts related to big data, big data analytics, business analytics, data-driven decision making, data governance, privacy, data products, lakehouse, data marketplace, firm operations, operating models, organisational structure, business processes, automation, supply chains, production operations, SMEs and performance.

Inclusion was guided by conceptual and empirical relevance to firm-level, organisational-level or operational-level transformation. Studies were treated as relevant if they explained mechanisms, boundary conditions or outcomes linking big data with operating models, decision systems, processes, supply chains, platforms or SMEs. Purely technical algorithm papers were considered only when their operational implications were clear. General commentary, marketing material, non-transparent consulting claims and studies without firm-level relevance were excluded from the core evidence base. Official policy materials were used only as institutional context where they clarify privacy, data sharing or industrial data access conditions. They were not treated as substitutes for firm-level evidence.

The synthesis was organised around six themes: data governance and privacy; data-driven decision making and organisational structure; process reconfiguration and automation; supply-chain and production operations; performance measurement and value realisation; and technology stacks, platform ecosystems and SME heterogeneity. The interpretive focus was operational mechanism rather than simple adoption. A study showing that top management support predicts analytics adoption is useful, but its theoretical value for this review depends on whether it explains how analytics changes decision routines, visibility, coordination or performance. This mechanism-oriented reading allows the review to integrate diverse studies into a coherent theory-building framework.

3. Big Data as Operating-Model Reconfiguration

The capability-performance view has provided an important foundation for big data research. Big data analytics capability is usually defined as a configuration of technology, data, human expertise, managerial capability and organisational routines that enables firms to acquire, process, analyse and act on data. Empirical studies and meta-analyses have linked such capability to firm performance, operational performance, innovation and decision quality (Ansari & Ghasemaghaei, 2023; Mikalef et al., 2019; Oesterreich et al., 2022). The field has therefore moved beyond the early question of whether big data matters. The more demanding question is how analytics capability is translated into changes in how firms operate.

The conventional capability-performance view has four limitations when used as the dominant framework. The first is causal compression. A claim that BDA capability improves performance combines many intervening organisational changes into one arrow. It does not reveal whether value comes from better forecasts, faster responses, more standardised processes, earlier detection of exceptions, stronger supplier coordination or more individualised service. The second is organisational abstraction. Capability measures often aggregate technology, skills, management support and culture into broad latent constructs. Such constructs are useful for modelling but can obscure where the transformation occurs in the operating model. The third is insufficient attention to institutionalisation. Data becomes actionable only when it is governed, trusted, discoverable, legally usable, semantically interpretable and linked to workflow authority. The fourth is weak treatment of heterogeneity. The same analytical architecture will not create identical value in retail, manufacturing, logistics, financial services or SMEs.

A more precise perspective treats big data as a force that reconfigures the operating model of the firm. An operating model refers to the way a company organises processes, roles, decision rights, technologies, data flows, controls, performance measures and interdependencies to execute its strategy. Big data changes this configuration in several ways. It improves observability by turning events that were previously invisible or late into analysable signals. It changes response speed by reducing the time between event occurrence, detection, interpretation and action. It alters authority relations by shifting some decisions from experience-based judgement to model-supported or automated routines. It changes process design by favouring standardised, instrumented and modular workflows. It also transforms cross-boundary coordination through shared dashboards, platform interfaces and data-driven supply-chain integration.

This operating-model perspective connects big data research with digital transformation theory. Digital transformation concerns organisational change induced by digital technologies that alters value creation and value capture (Vial, 2019). Big data is not one more tool within this transformation; it is an infrastructural condition for intelligent workflows, predictive operations, personalised services, algorithmic coordination and ecosystem data exchange. It also creates governance complexity, privacy responsibilities, model risk, data-quality vulnerabilities, skill gaps and tensions between central control and local responsiveness. These challenges are not peripheral. They are part of the transformation process itself.

The conceptual shift is from data possession to data operationalisation. Data possession means that firms hold datasets, platforms, tools and specialists. Data operationalisation means that data is converted into routine action. The former increases analytical potential; the latter changes the mechanics of work. A firm can perform analytics without redesigning decisions, and it can own large data assets without embedding them in processes. Conversely, a firm with limited internal analytics capacity may operationalise data effectively through platform dashboards, supplier portals, external analytics services or ecosystem tools. This distinction helps explain why big data produces asymmetric returns across firms and sectors.

4. Data Governance and Privacy as Operational Infrastructure

Data governance is often treated as a compliance or information-management concern, but the recent literature suggests that it should be understood as operational infrastructure. Big data without governance is fragmented, inconsistent, legally uncertain and difficult to trust. Nadal et al. (2022) show that governance across the data lifecycle is frequently manual or ad hoc, especially where organisations integrate heterogeneous and evolving data sources. Their work on operationalising and automating data governance is relevant for management research because it links data ingestion, transformation, integration, metadata and availability to the practical need to prepare reliable data for business users. Operationally, governance shapes whether a production manager trusts a quality signal, whether a logistics team can combine internal and external data, whether a service team can use customer information lawfully and whether a predictive model receives timely and standardised inputs.

The link between governance and process visibility is direct. Operational visibility is not achieved by collecting more data alone. It requires agreement on definitions, ownership, lineage, access rights, quality thresholds, timeliness and responsibility for correction. A warehouse delay may appear in transport management, inventory control, supplier communication, customer promise and financial penalty systems. If definitions, timestamps and identifiers differ across those systems, the firm may appear to see more while actually creating more confusion. Governance provides the institutional layer that makes data interpretable across functions.

Privacy research strengthens this argument. Gotsch and Schoegel (2023) show that the privacy paradox has an organisational dimension. Firms must balance value extraction from data with legitimacy, trust and regulatory conformance. These tensions directly affect operational use cases involving customers, employees, vendors or connected devices. Consent, purpose limitation, minimisation, access control and reuse rules are embedded in predictive maintenance, personalised service, employee scheduling, behavioural modelling and connected-product analytics. When privacy is treated as an afterthought, firms may build operational systems that later become legally fragile or reputationally damaging. When privacy is built into governance, firms can design workflows that are analytically useful and institutionally sustainable.

Data marketplaces and enterprise data marketplaces deepen the governance issue. Abraham et al. (2023) identify governance decision domains in data marketplaces, including quality, security, architecture, metadata, lifecycle, storage and pricing. Eichler et al. (2023) extend the logic to enterprise data marketplaces, whose goal is to democratise company data. From an operational standpoint, enterprise data marketplaces can reduce search costs, duplication and functional silos by making data products discoverable and reusable. Yet they require rules specifying who may publish data, who may consume it, how quality is certified, how usage is monitored and how incentives for sharing are created. Data democratisation without governance invites misuse; governance without democratisation preserves bottlenecks.

Policy developments reinforce the same logic. The OECD (2024) highlights the links among AI, data governance and privacy as firms face questions around lawful data use, risk management and international cooperation. The European Commission's Data Governance Act and Data Act stress trusted data sharing, data intermediaries, industrial data access and interoperability. For firms, these developments determine what operational data may be exchanged, reused, pooled or monetised across organisational boundaries. They also change the cost and design of analytics. Firms building operations around connected products, industrial machinery, customer data or external data markets must design their operating models around data-rights clarity and trust-based sharing.

The theoretical implication is that data governance should not be modelled only as an antecedent of analytics capability. It should be treated as a mediator between data availability and operational value because it turns raw data abundance into reliable operational visibility. Governance automation is therefore an important capability for data-intensive operations. Manual governance may work when data sources are limited and stable, but it struggles when firms manage many fast-changing and heterogeneous streams. Automated metadata management, lineage tracking, access control and data-quality monitoring are technical practices with direct operational consequences.

5. Data-Driven Decision Making and Organisational Structure

Big data transforms operations partly by changing how decisions are made. Data-driven decision making is not merely the use of dashboards or predictive models. It changes who has authority to decide, what counts as legitimate evidence, how exceptions are escalated, how uncertainty is interpreted and how responsibility is allocated. Janssen et al. (2017) argued that decision-making quality under big data depends on mechanisms that manage data veracity, variety and velocity. Li et al. (2022) later showed that analytics usage improves organisational decision quality through analytics capabilities. Together, these studies suggest that decision quality emerges from the interaction of data, capability, governance and routine.

Szukits and Móricz (2024) provide a useful bridge between analytics and organisation design. Their study links strategic emphasis on analytics, top management support, perceived data quality, analytical culture, data-driven decision making and centralisation in data use. The contribution is the recognition that analytics does not merely make decisions more rational; it changes information asymmetry and authority relations. Centrally managed and analytically standardised data can increase senior managers' visibility into local operations. At the same time, frontline managers may gain faster access to evidence that previously resided in specialised analytical departments. Big data can centralise oversight while decentralising evidence-based action.

Analytical culture deepens this issue. Karaboga et al. (2023) find that data-driven culture mediates the relationship between analytics management capability and operational and financial performance. This implies that capability is insufficient unless managers and employees accept data as a legitimate basis for action. Culture matters because operational decisions are often made under time pressure, incomplete information and competing incentives. A purchasing manager may resist model-based supplier recommendations because of long-standing relationships. A production supervisor may ignore predictive maintenance alerts when output targets are tight. A data-driven culture does not eliminate judgement, but it changes the burden of justification. Decisions that depart from evidence must be explained rather than assumed.

The centralisation question requires more nuance than much of the literature provides. Some centralisation is beneficial because it reduces duplicated datasets, standardises definitions, improves quality and aligns decisions across functions. Excessive centralisation may slow responsiveness, create analytical bottlenecks, detach models from local context and weaken learning at the operational edge. The relationship between centralisation and operational responsiveness may therefore be curvilinear. Low centralisation leaves fragmented data and inconsistent metrics. Moderate centralisation provides shared infrastructure and coherent governance while preserving local action. High centralisation can increase decision latency if operational teams must wait for central approval or specialist interpretation.

Data-driven decision making also changes escalation logic. In conventional operations, escalation often depends on hierarchy, personal experience or threshold-based reports. Under big data, escalation may be triggered by real-time anomalies, predicted risks, statistical control limits or confidence scores. This creates the possibility of decision-latency compression: the reduction in time between operational signal and managerial response. Many operational benefits of big data depend on this mechanism, including the prevention of stockouts, logistics rerouting, quality control, fraud detection, service-resource reallocation and customer churn intervention. Insight has limited value if it arrives after the operational window has closed.

A further issue is accountability. Big data can make deviations more visible, but visibility does not automatically clarify responsibility. Firms must decide whether accountability belongs to the data owner, model developer, process owner, decision maker or algorithmic system. When algorithm-supported decisions lead to poor outcomes, ambiguity arises: did the model fail, did the manager misinterpret the output, did the data pipeline deteriorate or did the context change? Future research should examine this accountability problem directly. The transformation of firm operations under big data is not only a question of better decisions; it is a redistribution of evidence, authority, responsibility and learning.

6. Process Reconfiguration and Automation

The operational significance of big data becomes most visible when it is embedded in processes. A process is not transformed because managers can analyse it after the event. Transformation occurs when data changes task sequencing, exception detection, resource allocation, quality control, customer service and feedback into redesign. Lehrer et al. (2018) show that BDA enables service innovation through affordances such as sourcing, storage, event recognition and prediction, behaviour recognition and prediction, rule-based action and visualisation. Their insight is that data does not merely inform service; it can become part of the service-production architecture.

This logic extends to production, logistics, procurement and customer operations. In production, data supports predictive maintenance, dynamic scheduling, defect detection, energy optimisation and capacity planning. In logistics, it supports routing, delivery prediction, fleet utilisation, warehouse slotting and risk alerts. In procurement, it supports supplier risk scoring, spend analysis, fraud detection and contract monitoring. In customer operations, it supports triage, churn prediction, personalisation and complaint escalation. In each domain, process transformation depends on instrumentation. A sensor reading, transaction record or customer click becomes operationally meaningful only when it is connected to a workflow that can act on it.

Automation is the most visible form of process reconfiguration, but it should not be treated as a universal endpoint. Automation produces the strongest gains in processes that are modular, repetitive, data-rich and governed by relatively stable rules, such as fraud screening, replenishment triggers, invoice matching, predictive maintenance alerts and routine quality inspection. In tacit, exception-heavy, ambiguous or politically sensitive processes, full automation may be inappropriate. The value of big data may lie instead in decision support, simulation, early warning or scenario analysis. Firms should therefore distinguish automation from augmentation. The more relevant question is not whether data can automate a process, but which parts of the process should be automated, which should be augmented and which require human judgement because of uncertainty, ethics, tacit knowledge or stakeholder consequences.

Process reconfiguration also involves exception detectability. Traditional operations rely on periodic reviews, manual inspections and lagging indicators. Big data allows firms to detect anomalies earlier and at lower levels of aggregation. A machine-learning system may identify a quality anomaly before it becomes a batch failure. A logistics platform may detect a delivery risk before a customer complains. A demand-sensing system may identify market shifts before a monthly planning cycle. Exception detectability matters because operational performance is often damaged by the delay between deviation and recognition. The faster and more variable the environment, the greater the value of early detection.

Data-driven process design also creates risks. Automation can amplify errors where data quality is poor or models are miscalibrated. Measurable signals can crowd out tacit knowledge. Employees may perceive analytics as surveillance rather than support. Algorithmic recommendations can reduce learning when users follow outputs without understanding their assumptions. Process transparency can become process control, raising questions of autonomy and trust. These risks show why social and governance alignment are inseparable from efficiency. Data-driven process design changes the relationship among workers, managers, technologies and performance systems.

A useful research direction is process modularity. Modular processes have repeatable units, clear inputs, outputs and performance criteria. They are more amenable to instrumentation and automation. Highly interdependent processes with tacit coordination, ambiguous objectives or unstable task boundaries require different analytics designs. Future studies should compare modular and non-modular processes, routine and exception-heavy workflows and standardised and customised services. This would move the field away from general claims that analytics improves operations toward more precise explanations of where and why it does so.

7. Supply-Chain and Production Operations

Supply-chain and production operations offer clear evidence that big data changes operational coordination. Supply chains generate data from suppliers, logistics providers, production systems, retailers, customers, market signals and external risk sources. They also require coordination across organisational boundaries, making them sensitive to data quality, timeliness and trust. Lee and Mangalaraj (2022) show that big data analytics supports supply-chain management through forecasting, logistics, inventory, risk management, sustainability and performance improvement. Gopal et al. (2024) evaluate big data practices such as machine learning, cloud computing, RFID, blockchain, IoT, ERP and business intelligence against criteria including supplier integration, customer integration, cost, utilisation, flexibility, demand management, time and value. These studies point to a shift from optimising individual functions to synchronising data across actors.

The main mechanism is process visibility. In supply chains, visibility means observing demand, inventory, production status, transport flows, supplier reliability and customer requirements across time and organisational boundaries. Big data expands visibility by combining internal transaction records with external signals, connected devices and platform data. Yet visibility is not equivalent to transparency. Firms may see more data without knowing whether it is reliable, comparable or actionable. Cross-boundary visibility requires shared definitions, platform interfaces, data-sharing agreements and trust. This connects supply-chain analytics to governance research: inter-organisational data sharing cannot be sustained if partners fear opportunistic use, quality manipulation, loss of bargaining power or privacy exposure.

Forecasting and demand management illustrate the operational logic. Traditional forecasting depends on historical sales, periodic updates and hierarchical planning cycles. Big data enables demand sensing through real-time sales, search behaviour, weather signals, mobility data, events and platform interactions. The value is not only higher forecast accuracy. It is the ability to adjust production, inventory, replenishment and logistics before demand deviations become costly. This is decision-latency compression at the supply-chain level. Yet forecasting improvements will not translate into performance if procurement lead times, production flexibility, supplier responsiveness or logistics capacity remain rigid. Analytics value requires complementary operational flexibility.

Production operations reveal the same knowledge-action gap. Predictive maintenance can reduce downtime only if maintenance teams can act on alerts, spare parts are available and schedules allow intervention. Quality analytics can identify defects only if process engineers translate patterns into corrective action. Energy analytics can optimise consumption only where equipment and production requirements permit adjustment. Big data creates value when analytical insight is matched by operational capacity to respond. This matching condition is under-theorised in survey research that measures analytics capability and performance outcomes without measuring responsiveness.

Resilience has become a central theme. Lin et al. (2025) show that organisational resilience mediates the relationship between BDA capability and firm performance and that environmental dynamism shapes this relationship. This shifts attention from static efficiency to adaptive capacity. In stable settings, analytics may improve cost, quality and utilisation. Under disruption, value may arise through early warning, scenario analysis, rapid reconfiguration, alternative sourcing, inventory repositioning and customer communication. The meaning of performance is therefore contingent: firms may obtain value not by optimising a steady-state process but by adapting under turbulence.

The supply-chain literature also reveals the importance of platform architectures. Many firms do not collect all relevant supply-chain data internally. They depend on logistics platforms, e-commerce platforms, supplier portals, IoT ecosystems and third-party data providers. Platform-mediated coordination can improve visibility and lower transaction costs, but it can also create dependency, data asymmetry and governance challenges. Large firms may develop proprietary data-integration architectures; SMEs may rely on platform analytics. This difference links supply-chain transformation to firm-size heterogeneity and ecosystem governance.

8. Performance Measurement and Value Realisation

Performance is the most common outcome in big data research, yet it remains conceptually uneven. Some studies examine financial performance, others examine operational performance, innovation, decision quality, supply-chain performance, resilience or customer outcomes. Ansari and Ghasemaghaei (2023) meta-analysed the relationship between BDAC and firm performance, including moderators such as performance type, country and respondent type. Oesterreich et al. (2022) conducted a broader meta-analysis and conceptualised BDA as a socio-technical system in which technical and social factors jointly create business value. These findings are important, but they also show that performance should not be treated as a single endpoint.

Big data creates value through at least five pathways. Efficiency value arises through cost reduction, faster cycles, improved resource utilisation, reduced waste and fewer manual interventions. Quality value arises through defect detection, process standardisation, root-cause analysis and service consistency. Responsiveness value arises through faster sensing, shorter decision latency and dynamic adjustment. Innovation value arises through new services, individualised offerings, data-based business models and experimentation. Resilience value arises through disruption detection, alternative planning, adaptive coordination and recovery speed. Treating all these pathways as general firm performance obscures the mechanisms through which big data works.

Industry characteristics shape these pathways. Mueller et al. (2018) show that the effect of BDA on performance varies by industry characteristics. Industries differ in data intensity, process digitisation, regulation, capital intensity, customer interaction frequency and supply-chain complexity. In digital retail, behavioural data may directly influence pricing, assortment, promotion and service. In manufacturing, sensor data may operate through maintenance, quality and scheduling. In financial services, governance and privacy may condition data use. In logistics, route and location data reshape coordination. A universal performance model will miss these sectoral mechanisms.

Grover et al. (2018) distinguish value creation from value realisation, a distinction that remains essential. Value creation refers to the generation of insight, capability or operational potential. Value realisation refers to the capture of measurable benefits through organisational action. Firms often create insight without realising value because they do not redesign incentives, authority, workflows or measurement systems. A churn model creates value only when service teams can intervene, offers are viable, contact rules permit action and outcomes are measured. A predictive maintenance model creates value only when scheduling and spare-parts logistics can respond.

A stronger measurement agenda would separate leading, intermediate and lagging indicators. Leading indicators include data quality, availability, governance automation, analytical literacy, model deployment and process instrumentation. Intermediate indicators include process visibility, decision latency, exception-detection rate, forecast-adjustment speed, automation depth and coordination frequency. Lagging indicators include cost, quality, customer retention, delivery reliability, innovation output, resilience and financial performance. This layered approach would help researchers avoid attributing performance changes to analytics capability when the operational mechanism is unmeasured. It would also help managers diagnose where value leakage occurs.

9. Data Platforms, Ecosystems and SME Heterogeneity

Technology architecture is often underrepresented in management reviews of big data, yet it matters because it determines what data can be combined, how quickly insights are produced, how expensive analytics becomes and how easily operational users can access data products. Recent work on lakehouses, enterprise data marketplaces and data products suggests that firms are moving from isolated warehouses and data lakes toward integrated and platformised data environments. Armbrust et al. (2021) argue that lakehouse architectures combine features of data warehouses and data lakes while addressing problems such as staleness, reliability, cost, lock-in and limited use-case support. Schneider et al. (2024) review lakehouse concepts and technologies and note that such architectures seek to simplify enterprise analytics environments that suffer from replication, slow processes and high operating cost.

The operational implications are substantial. If data is scattered across disconnected systems, managers rely on stale reports or manually reconciled spreadsheets. If data is centralised but not curated for operational use, business users remain dependent on specialists for routine questions. If architecture supports reusable data products, governed access, lineage and integration with workflows, operational teams can use data more directly. Architecture therefore shapes decision latency, visibility and scalability. A successful pilot analytics project may fail to transform operations if the underlying platform cannot support repeated deployment across functions and units.

Enterprise data marketplaces add an organisational layer to architecture. Eichler et al. (2023) conceptualise the enterprise data marketplace as a platform for democratising company data. Such marketplaces make data assets discoverable, requestable and reusable. For operations, this can reduce friction between data producers and users. Production teams may discover supplier-quality data maintained by procurement; logistics teams may use customer-delivery preference data maintained by sales; service teams may reuse product telemetry maintained by engineering. These flows are central to operating-model reconfiguration, but they require incentives and governance. Data producers may not document or improve assets if they receive no benefit from reuse. Data consumers may misuse assets if metadata and restrictions are unclear.

Big data operations are increasingly ecosystem-based. Firms depend on external platforms for sales, logistics, payments, advertising, cloud computing and analytics. Platform dependence expands data access but can reduce autonomy. This is particularly relevant for SMEs. Bar-Gill et al. (2024) show in a field experiment on eBay that access to a data-rich seller dashboard increased revenues for e-retailers, partly through active performance monitoring. This evidence matters because it shows that small firms can capture analytics value without building full internal infrastructure. The platform supplies data and interface routines; the SME supplies managerial attention and operational action.

SME research challenges the assumption that smaller firms are simply less mature versions of large firms. Babalghaith and Aljarallah (2024) identify technological, organisational and environmental determinants of BDA adoption in SMEs, including compatibility, complexity, uncertainty, top management support, organisational readiness and data-driven culture. Bhatti et al. (2025) show that BDA capabilities improve MSME innovation and performance through digital platform and network capabilities. This double mediation logic is theoretically significant. It suggests that SMEs may gain value not by internalising all components of a large-firm analytics stack but by using analytics to participate more effectively in platforms and networks.

This distinction calls for an ecosystem-based capability view. In traditional resource-based logic, capability tends to reside inside the firm. In platformised data environments, capability may be distributed across cloud providers, marketplaces, software vendors, logistics platforms, e-commerce platforms and partners. A firm's operating model is shaped by how well it orchestrates these distributed analytical resources. The key questions become: who controls the data, who defines the metrics, who owns the models, whether data is portable and whether platform analytics serves the firm's goals, the platform owner's goals or both. These questions should be central to future studies of big data and firm operations.

10. Integrated Discussion: The Data-to-Operations Reconfiguration Framework

The reviewed literature supports an integrated framework explaining how big data transforms firm operations. The Data-to-Operations Reconfiguration Framework consists of three upstream components, four mechanisms, five outcome domains and four boundary conditions. The upstream components are data institutionalisation, decision-system redesign and operational embedding. The mechanisms are process visibility, decision-latency compression, exception detectability and cross-boundary coordination. The outcome domains are efficiency, resilience, innovation, service personalisation and financial value. The boundary conditions are industry data intensity, regulatory burden, SME constraints and environmental dynamism.

Data institutionalisation converts dispersed digital traces into governed, trusted, accessible and legally usable assets. It includes governance, privacy, quality, metadata, lineage, architecture, access rights and platform arrangements. This component is supported by governance research (Abraham et al., 2023; Eichler et al., 2023; Nadal et al., 2022), privacy research (Gotsch & Schoegel, 2023) and policy developments around data sharing and industrial access (European Commission, 2024, 2025; OECD, 2024). Data institutionalisation is foundational because operations depend on reliable and timely signals. Without it, data abundance may increase noise, risk and inconsistency.

Decision-system redesign refers to changes in evidence standards, decision rights, analytical culture, centralisation, escalation logic and accountability. It explains why some firms obtain value from analytics while others produce unused dashboards.

Data must enter managerial routines. It must change what managers attend to, how quickly they act, how they justify decisions and how learning occurs after outcomes are observed. Operational embedding then integrates data and analytics into workflows, automation, process controls, supply-chain interfaces, service systems and performance measures. This is the point at which analytics becomes work. A model that remains in a data-science environment does not transform operations; a model embedded in replenishment, maintenance, routing, customer triage or supplier risk management can do so.

The first mechanism is process visibility. Big data increases visibility when it allows firms to observe process states, dependencies, deviations and performance drivers at greater granularity and speed. Visibility changes control because firms can compare units, identify bottlenecks and coordinate interventions. It may improve accountability, but it can also create surveillance concerns and defensive behaviour. The second mechanism is decision-latency compression. Many operational benefits depend on the speed with which firms move from signal to action. Big data can reduce latency through automated data collection, alerts, predictive models and real-time dashboards, but only when decision rights and operational capacity permit action.

The third mechanism is exception detectability. Operations fail not only because firms lack information but because they recognise exceptions too late. Big data enables earlier detection of anomalies, supplier disruptions, demand shifts, fraud, dissatisfaction and equipment risk. Exception detectability also raises design problems: false positives, alert fatigue, threshold selection and trust in models. The fourth mechanism is cross-boundary coordination. Big data allows functions, business units, suppliers, platforms and customers to coordinate around shared signals. This mechanism is central to supply chains and ecosystems, but it depends on interoperability, common metrics, trust and governance.

The framework generates six propositions for future empirical research. Proposition 1: data governance quality improves operational value primarily through process visibility and decision-latency compression rather than through a direct effect on performance. Proposition 2: centralisation in data use moderates the relationship between analytical culture and operational responsiveness in a curvilinear way; moderate centralisation improves coherence, while excessive centralisation slows response. Proposition 3: platformised data architectures increase coordination capacity, which improves supply-chain resilience and process synchronisation. Proposition 4: automation produces stronger gains in modular, repetitive, data-rich processes than in tacit or exception-heavy processes. Proposition 5: SMEs capture greater value when BDA is complemented by digital platform capability and network capability than when they pursue closed internal analytics stacks. Proposition 6: under high environmental dynamism, big data affects performance mainly through resilience and reconfiguration speed rather than through static efficiency alone.

These propositions shift the unit of analysis. Instead of asking whether BDA capability improves firm performance, researchers can ask which mechanism is activated, in which process domain, under which governance arrangement and with which contextual constraints. This move is essential for theoretical advancement. The field does not need another generic claim that big data improves performance; it needs precise explanations of how data reorganises operating models.

11. Research Gaps and Future Agenda

Several gaps follow from the synthesis. The first concerns governance-mediated operational value. Data governance and operations research remain insufficiently connected. Governance studies focus on quality, metadata, ownership, privacy and access, while operations studies focus on forecasting, automation, supply-chain performance and process improvement. Future research should test whether governance automation improves visibility, whether metadata quality reduces decision latency, whether privacy-by-design increases sustainable data reuse and whether enterprise data marketplaces improve cross-functional coordination.

The second gap concerns decision-right redistribution. Existing research recognises analytical culture and centralisation, but more work is needed on how big data reallocates authority. Does analytics empower frontline workers or strengthen central monitoring? Under what conditions does centralised data governance coexist with decentralised operational action? How should firms design escalation rules when model-generated alerts conflict with managerial judgement? These questions require qualitative studies, field experiments and longitudinal designs that capture decision practices rather than only survey perceptions.

The third gap concerns micro-foundations of process embedding. Many studies measure analytics capability at firm level, but process transformation occurs at the level of workflows, tasks, roles and routines. Future research should examine how specific processes are instrumented, how employees interpret analytics, how models are integrated into workflow systems and how feedback loops are maintained. Process mining, digital trace data, ethnographic observation and mixed-method research could provide stronger evidence than cross-sectional survey models alone.

The fourth gap concerns platform dependence and ecosystem governance. As firms rely on external platforms for analytics, data access and operational coordination, capability becomes distributed. Research should examine whether platform analytics reduces capability gaps for SMEs, whether it creates dependency, how data portability affects autonomy and how platform owners influence the metrics firms use to manage operations. This line of inquiry is practically important because many SMEs will not build large internal data-science teams but will operate through platform analytics.

The fifth gap concerns resilience and dynamic environments. Literature has begun to link BDA with organisational resilience, but more work is needed to distinguish efficiency-oriented and resilience-oriented value. In stable environments, analytics may optimise existing operations. In turbulent environments, it may support sensing, adaptation, reconfiguration and recovery. Future studies should measure disruption frequency, adaptation speed, recovery quality and environmental dynamism. They should also examine whether firms over-invest in efficiency analytics while under-investing in resilience analytics.

The sixth gap concerns negative consequences and trade-offs. Big data operations can produce surveillance, privacy risk, algorithmic rigidity, model dependence, alert fatigue, data-quality vulnerabilities and power asymmetries. The same visibility that improves coordination may increase employee stress. The same platform dashboard that improves SME revenue may deepen platform dependence. The same automation that reduces cost may reduce local learning. Future research should examine the conditions under which big data transformation creates operational fragility rather than resilience.

12. Practical Implications and Conclusion

For executives, big data transformation should be governed as operating-model redesign rather than as an IT programme. Investment in cloud infrastructure, analytical tools or data-science talent will not transform operations unless decision rights, workflows, incentives and performance measures are redesigned. Senior leaders should ask four diagnostic questions: which operational decisions are too slow, which processes are insufficiently visible, which exceptions are detected too late and which organisational boundaries prevent coordination. These questions are more useful than asking only whether the firm has adopted advanced analytics.

For data and technology leaders, architecture should be evaluated by operational usability. A sophisticated platform has limited value if operational teams cannot discover, trust and act on data assets. Governance should be automated where possible, metadata should be readable by business users and data products should be linked to decision use cases. Enterprise data marketplaces should not become catalogues of poorly documented assets. They should become governed interfaces between data producers and operational users.

For operations managers, analytics should be embedded selectively. Not every process should be automated. Managers should distinguish processes suitable for full automation, processes suitable for decision augmentation and processes requiring human judgement. They should monitor decision latency, exception detection, alert quality and workflow adoption, not only final performance outcomes. For SMEs, value does not necessarily require a complete internal analytics stack. SMEs can capture value through platform dashboards, external analytics services, network relationships and disciplined routines, while also monitoring data portability and dependency risks.

The transformation of firm operations under big data is not a linear story of technology adoption followed by performance improvement. It is a reconfiguration of the operating model. Data must be institutionalised through governance, privacy, quality and architecture; it must reshape decision systems through analytical culture, evidence standards, decision rights and accountability; and it must be embedded into processes through instrumentation, automation, workflow redesign, supply-chain integration and platform orchestration. When these translations occur, big data creates operational value through visibility, latency compression, exception detectability and coordination. The Data-to-Operations Reconfiguration Framework provides a more precise lens than the conventional capability-performance view because it explains how data becomes organised, governed, enacted and sustained as operational value.

Funding

No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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