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DEVELOPMENT OF A METHODOLOGY FOR APPLYING BIG DATA AND IOT TECHNOLOGIES IN SUPPLY CHAIN MANAGEMENT

https://doi.org/10.5281/zenodo.21208280

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Abstract: *The digitalization of supply chain management is shifting managerial logic from retrospective accounting toward continuous observation, forecasting, and predictive-prescriptive control. In this context, the Internet of Things provides real-time primary data on the condition of objects, cargo, transport, warehouses, and production assets, whereas Big Data ensures the integration, storage, processing, and analysis of high-volume, heterogeneous, and fast-arriving data for decision-making. The purpose of this article is to develop a methodology for applying Big Data and IoT technologies in supply chain management on the basis of current scientific and industry evidence. The study relies on analytical synthesis of literature on Supply Chain 4.0, Big Data analytics, IoT-enabled visibility, digital logistics, and technology implementation risks. The results show that Big Data and IoT are complementary rather than alternative technologies: IoT generates factual event streams, while Big Data converts them into managerial decisions. The most mature application domains are demand forecasting, transport monitoring, inventory management, cargo condition control, route optimization, and risk management. A layered data architecture and a nine-stage implementation methodology are proposed, including diagnosis, use-case prioritization, data mapping, IoT deployment, Big Data platform creation, model development, managerial integration, piloting, and governance. The article also systematizes operational, economic, visibility, resilience, and ESG indicators for performance assessment. It is concluded that the key effect is achieved not by data collection alone, but by embedding analytics into the operational contour of supply chain management.*

Keywords: *Big Data, Internet of Things, supply chain management, Supply Chain 4.0, demand forecasting, transport monitoring, inventory management, route optimization, data architecture, digital logistics*

INTRODUCTION

The digitalization of supply chain management is shifting the focus of management from retrospective accounting of operations to continuous observation, forecasting, and predictive-

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prescriptive control. Within this logic, the Internet of Things ensures the collection of primary real-time data on the condition of objects, cargo, transport, warehouses, and production assets, while Big Data provides the integration, storage, processing, and analytics of high-volume, heterogeneous, and rapidly generated data for decision-making. The literature indicates that the combination of IoT and Big Data forms the basis of Supply Chain 4.0 or Supply 4.0, that is, a digital supply chain characterized by high transparency, adaptability, and resilience [1], [2], [3], [10]. In the supply chain context, Big Data is commonly interpreted through the 5V characteristics: volume, velocity, variety, veracity, and value [4]. These data originate from ERP, WMS, TMS, MES, and CRM systems, from orders and sales, inventory balances, procurement and transport operations, sensors, RFID, GPS, and external sources such as weather, traffic, market signals, and social media [4], [5], [10]. IoT in supply chain management is understood as a network of physical objects equipped with sensors, RFID/NFC tags, GPS and telematics, and communication and identification tools, making it possible to track location, condition, status, movement, and environmental parameters in real time [1], [2], [7], [8]. The complementarity of the two technologies is methodologically significant. IoT without analytics produces a raw stream of observations, whereas Big Data without IoT is often limited to transactional records. Their joint use creates a closed managerial loop: collection, transmission, storage, processing, forecasting or optimization, managerial action, and feedback. This logic explains why the role of these technologies extends beyond automation and becomes central to data-driven supply chain management. Several theoretical lenses are suitable for studying this transformation. The SCOR model links digital technologies to the Plan, Source, Make, Deliver, Return, and Enable processes, and research on Big Data analytics in supply chains indicates that the most active support concerns Deliver and Enable, followed by Plan [3]. The Dynamic Capabilities View treats Big Data and IoT as capabilities for sensing, seizing, and reconfiguring [3]. Organizational Information Processing Theory explains how digital technologies increase the ability of supply chains to cope with uncertainty through improved visibility and faster information processing [3]. For implementation analysis, the TOE and HOT-fit frameworks are especially useful, particularly in relation to the barriers to Big Data analytics and IoT adoption [6]. Against this background, the purpose of the article is to develop a methodology for applying Big Data and IoT technologies in supply chain management, including the identification of application domains, the design of a data and analytics architecture, the specification of implementation stages, and the systematization of performance indicators.

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Methods

The study is based on analytical synthesis of academic and industry sources addressing IoT in supply chains, supply chain visibility, Big Data analytics, predictive demand forecasting, optimization and management of Big Data in supply chains, risks of Big Data analytics implementation, digital logistics, route optimization, and sectoral use cases in logistics, food chains, and healthcare [1]–[17]. Methodologically, the article combines four analytical perspectives. First, a process perspective is used to align Big Data and IoT with core supply chain tasks, including forecasting, transport monitoring, inventory control, cargo condition monitoring, routing, and risk management. Second, an architectural perspective is applied to structure the data environment into sensing, connectivity, ingestion, storage, processing, analytics, application, and governance layers. Third, an implementation perspective is employed to derive a staged methodology for adoption, based on diagnosis, prioritization, platform creation, model deployment, and governance. Fourth, an evaluation perspective is used to organize key performance indicators into operational, economic, visibility, resilience, and ESG-related dimensions. The study does not introduce external empirical evidence beyond the cited material. Its contribution lies in integrating the existing conceptual, technological, and practical findings into a coherent methodological framework suitable for scientific analysis and practical deployment.

RESULTS

The results of the analysis indicate that Big Data and IoT should be treated as complementary technologies that jointly support a closed-loop model of supply chain control. IoT creates a real-time factual flow of observations concerning assets, cargo, vehicles, warehouses, and equipment, whereas Big Data transforms these heterogeneous data streams into descriptive, diagnostic, predictive, and prescriptive managerial outputs.

The literature shows that this technological combination addresses several mature supply chain tasks. In demand forecasting, the relevant data include historical sales, prices and promotions, seasonality, weather, web and social media signals, customer behavior, and equipment and spare-parts status [4], [10]. Typical models include ARIMA and ETS, regression, decision trees, random forest, SVM, neural networks and LSTM, and Bayesian networks [3], [4]. The expected effect is improved forecast accuracy, reduced forecasting error, and lower levels of shortage and excess inventory. McKinsey estimates the potential reduction of forecast error at 30–50% when advanced analytics and external factors are used [12]. In transport monitoring, IoT supports location tracking, ETA prediction, route deviation control, speed and dwell-time monitoring, and monitoring of transport conditions through GPS, telematics, onboard

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sensors, traffic data, and TMS and WMS events [1], [7], [8]. A widely cited example is UPS ORION, which uses GPS together with historical and current transport data for dynamic routing. The company estimates the effect at savings of 100 million miles and 10 million gallons of fuel per year [14]. According to sectoral evidence, full ORION deployment was expected to reduce operating costs by USD 300–400 million annually [15]. In inventory management, Big Data and IoT make it possible to observe actual stock levels and movement in real time, connect replenishment policy with probabilistic demand forecasting, reduce safety stock, and manage multi-echelon inventory [4], [12]. The expected effect is lower inventory, higher fill rate, and fewer stock-outs. McKinsey evaluates the inventory reduction potential in Supply Chain 4.0 as highly significant, reaching up to 75% in some mature digitalization scenarios [12]. In cargo condition control, the most relevant application areas are food and cold chains, pharmaceuticals, chemicals, and highly sensitive electronics. The monitored parameters include temperature, humidity, vibration, shock loads, and tampering [1], [7], [8]. In the Yumchop Foods case, IoT sensors and a notification system were used to monitor the temperature and humidity of frozen products in order to reduce losses and maintain quality [17]. Route optimization uses order data, customer geography, time windows, road conditions, transport constraints, telematics, and route history [12], [14]. Typical methods include the vehicle routing problem and its modifications, dynamic routing, prescriptive analytics, and digital twins of transport networks. The expected effects are lower mileage, fuel consumption, delivery time, and idle time [14], [15]. Big Data and IoT also support risk reduction and resilience enhancement by identifying early disruption signals, tracking suppliers, controlling bottlenecks, forecasting cold-chain violations, and assessing cyber and operational risks [3], [6], [9]. The World Economic Forum notes that more than 75% of companies experienced insufficient end-to-end visibility across supply chains, which slowed their response to disruptions [11]. A practically grounded data architecture for supply chain management can be represented as an eight-layer structure. The first layer is perception or sensing, including RFID, GPS, sensors, telematics, and PLC/controllers. The second is connectivity, including Wi-Fi, LPWAN, 4G/5G, API, MQTT, and EDI. The third is data ingestion, including ETL/ELT, event streaming, and message bus mechanisms. The fourth is storage, including data lake or lakehouse, time-series databases, data warehouses, and master data. The fifth layer is processing, covering batch and stream processing, cleansing, normalization, and feature engineering. The sixth layer is analytics, including descriptive, diagnostic, predictive, and prescriptive analytics. The seventh is the application layer, including

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control towers, dashboards, alerts, APS/S&OP, and TMS, WMS, and ERP integration. The eighth layer is governance and security, including access rights, data quality, data catalogues, cyberprotection, and audit. In parallel, IoT architecture is described in some studies as a four-layer model consisting of sensor or perception, networking, service or computation, and application or user interface [7], [8]. For supply chain research, it is methodologically useful to integrate this IoT view with a Big Data platform architecture. The reviewed sources also allow the systematization of analytical models by supply chain task. Demand forecasting is associated with ARIMA, XGBoost, random forest, LSTM, and Bayesian networks. ETA and transport monitoring rely on anomaly detection, ETA models, and streaming analytics. Inventory management uses probabilistic replenishment models and multi-echelon optimization. Cargo condition control uses rule-based alerts and spoilage prediction. Route management uses vehicle routing models, dynamic routing, genetic algorithms, and prescriptive optimization. Risk management uses risk scoring, scenario modelling, simulation, and digital twins.

The advantages of Big Data and IoT can be grouped into operational, economic, and strategic effects. Operationally, the technologies increase transparency, reduce response time, improve planning accuracy, lower logistics and warehousing costs, reduce idle time, and improve OTIF and service level [1], [3], [11], [12]. Economically, they reduce transport and storage costs, limit losses caused by shortage and overstocking, improve the return on digital operations, and reduce write-offs and spoilage [12], [14], [17]. Strategically, they increase resilience and adaptability, support the transition to data-driven supply chain management, improve interaction with suppliers and customers, and create the conditions for platform business models [9], [11], [12]. At the same time, the barriers remain substantial. The most important constraints are poor data quality, fragmented systems and weak integration, high initial investment, competence shortages, resistance to change, lack of unified standards, and privacy and cybersecurity risks [3], [5], [6], [9], [11]. In the study of implementation risks of Big Data analytics in sustainable supply chains, technological risks were identified as the most significant, followed by human and organizational risks [6]. Successful implementation therefore requires a clear business objective, prioritization of use cases according to effect and feasibility, mature data management, integrated architecture instead of disconnected pilots, top-management support, a cross-functional team involving logistics, IT, analytics, procurement, and production, cybersecurity by design, and a logic of piloting and scaling rather than a one-time big bang [3], [6], [12], [13], [15]. The international and sectoral experience reinforces these conclusions. UPS

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ORION illustrates the logistics and last-mile use of data-driven routing, with more than 200 parameters collected daily from 80,000 vehicles and strong implications for change management, metric revision, and data governance [14], [15]. Maersk identifies IoT as one of the key trends in logistics, associating it with real-time tracking, predictive maintenance, inventory management, and route optimization. According to the company's estimates, IoT can yield performance improvements of 10–20% in the short term and 20–40% within a 2–4-year horizon [16]. In the food chain, IoT supports temperature monitoring, spoilage prevention, waste reduction, and quality confirmation [1], [7], [17]. In healthcare and pharmaceuticals, IoT combined with blockchain is used for tracking medical products and controlling transport conditions, and in vaccine supply chains IoT, blockchain, and machine learning are used jointly for chain management and demand prediction [9], [10]. According to a McKinsey survey of more than 250 logistics leaders, 87% of shippers maintained or increased digital investments since 2020, and 93% plan to maintain or expand such investments over the next three years [13]. This indicates that the technologies have moved beyond experimental local solutions and are becoming part of baseline competitiveness. On the basis of the reviewed evidence, a nine-stage methodology for applying Big Data and IoT in supply chain management can be developed. The first stage is supply chain diagnosis and goal setting, using SCOR analysis, digital maturity audit, bottleneck mapping, and baseline KPI to identify problems such as forecast error, stock-out, spoilage, low visibility, and high transport cost. The second stage is use-case prioritization according to strategic significance, expected economic effect, data readiness, integration complexity, payback period, scalability, risk, and security compliance. Recommended initial use cases are demand forecasting, transport monitoring, cold-chain control, inventory optimization, and route optimization.

The third stage is data map design, including the identification of observed objects, monitored parameters, measurement frequency, data origin, data ownership, destination systems, source catalogue, identifier model, and data quality requirements. The fourth stage is IoT contour deployment, including the selection of sensors, RFID, GPS, and gateways, the configuration of transmission protocols, the design of edge-cloud interaction, and calibration and reliability testing, with special attention to stream continuity, latency reduction, and rules for reacting to deviations. The fifth stage is the creation of the Big Data platform, requiring a unified repository, ingestion mechanisms, stream and batch processing, a business-logic layer, and visualization and alerting tools, based on the principle of a single source of truth for supply chain participants. The sixth stage is the

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development of analytical models, where each use case requires a defined target variable, features, recalculation frequency, quality metric, and integration rules. Illustrative metrics include MAPE or WAPE for demand forecasting, MAE for ETA, precision and recall for spoilage incidents, and cost per route, kilometre, or stop for route optimization. The seventh stage is the integration of models into the managerial contour. The key principle is that analytics must change the operational decision: demand forecast should affect replenishment, sensor signals should generate control-tower alerts, ETA deviations should trigger unloading window replanning, and supplier risk should lead to sourcing-plan revision. The eighth stage is piloting and scaling, ideally on one warehouse, one region, one product type, or one transport category, followed by before-and-after comparison, ROI analysis, identification of organizational barriers, and network-level scaling. The ninth stage is continuous improvement and governance, including data owners, model owners, retraining procedures, SLA for data quality, cybercontrol, algorithm audit, and explainability.

The effectiveness of implementation should be assessed through a multi-level KPI system. Operational indicators include MAPE or WAPE of demand forecasting, OTIF, order cycle time, stock-out rate, fill rate, inventory turnover, days of inventory, spoilage rate, ETA error, and transport utilization. Economic indicators include logistics cost per order, transport cost per ton-kilometre, warehousing cost per unit, inventory holding cost, cost of lost sales, ROI, payback period, and total cost to serve. Visibility and data indicators include the share of tracked shipments, data latency, completeness and accuracy of master data, sensor uptime, false positive and false negative alerts, and model drift frequency. Resilience and risk indicators include time-to-detect disruption, time-to-respond, time-to-recover, supplier risk exposure, cold-chain excursion frequency, and number of cyber incidents. ESG indicators include fuel consumption, CO_2 per shipment, waste and spoilage reduction, and returns caused by damage or violation of storage conditions.

Discussion

The results demonstrate that Big Data and IoT should not be analyzed as separate technological trajectories. Their managerial value emerges through integration: IoT provides factual, time-sensitive visibility, while Big Data makes it possible to process this visibility into forecasting, optimization, and response. This explains why the key effect lies not in data accumulation itself, but in embedding analytics into the operational contour of supply chain management. The SCOR, Dynamic Capabilities, Organizational Information Processing, and TOE or HOT-fit perspectives help clarify different aspects of this process. SCOR links the technologies to specific process domains, Dynamic Capabilities explains their role in sensing, seizing, and

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reconfiguring, Organizational Information Processing Theory clarifies their contribution to uncertainty reduction, and TOE and HOT-fit explain why implementation success depends on technological, organizational, environmental, and human fit [3], [6]. Together, these frameworks support the view that the methodological design of Big Data and IoT applications must encompass processes, data, architecture, organizational readiness, and governance. The empirical and industry evidence synthesized in the study also suggests that the most mature applications are concentrated where real-time data and analytics can be directly translated into operational decisions. Demand forecasting, route optimization, transport monitoring, cold-chain control, and inventory management are therefore not only common use cases but also the most methodologically defensible starting points for implementation. Their maturity is reinforced by quantified results reported in the reviewed material, including forecast error reduction potential, inventory reduction, route-efficiency savings, and productivity gains [12], [14], [15], [16].

At the same time, the main constraints are not purely technical. Data quality, integration, competence shortages, resistance to change, and cybersecurity remain structural barriers [3], [5], [6], [9], [11]. This supports the conclusion that a scientifically grounded methodology must include both technical architecture and organizational governance. A fragmented pilot logic without integration, ownership, and scaling mechanisms is unlikely to generate end-to-end supply chain effects. The proposed methodological sequence—diagnosis, use-case prioritization, data map, IoT contour, Big Data platform, analytical models, managerial integration, pilot scaling, and governance—therefore represents not only a deployment sequence but also a managerial logic that connects data generation with value creation. In this sense, methodological rigor in Big Data and IoT deployment is inseparable from data governance, process redesign, and performance measurement.

Conclusion

Big Data and IoT are complementary rather than alternative technologies in supply chain management. IoT creates a continuous flow of factual data about cargo, vehicles, inventories, warehouses, and equipment, while Big Data transforms these data into descriptive, predictive, and prescriptive managerial outputs. The most mature application areas are demand forecasting, transport monitoring, inventory management, cargo condition control, route optimization, and risk management. The strongest effects arise when analytics are embedded into operational decisions, rather than used only for passive observation. The reviewed evidence shows that quantified gains may include substantial reductions in forecast error and inventory, major savings in miles, fuel, and operating costs in routing

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systems, and meaningful performance improvements in logistics operations. A scientifically and practically grounded methodology for applying Big Data and IoT in supply chain management should therefore include diagnosis, use-case prioritization, data architecture, IoT deployment, Big Data platform development, analytical model design, integration into the managerial contour, KPI-based evaluation, piloting, scaling, and governance. Performance assessment should be multi-level and include operational, economic, visibility, resilience, and ESG indicators. The central conclusion is that the main value of Big Data and IoT does not reside in data collection alone, but in the ability to turn continuous digital signals into coordinated, timely, and economically justified supply chain decisions.

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