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Supply Chain Optimization Using Industrial Data Analytics

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Abstract: Demand for supply chain optimization through industrial data analytics has surged, fueled by lessons learned during the COVID-19 crisis. A systematic review of methods applied in practice in 2021 summarizes how data science and operations research techniques are being adopted to tackle key issues. The review follows the ground-up flow of data in a typical supply chain. Publications describe predictive maintenance; end-to-end supply chain visibility; and inventory optimization. The data sources and processes for these analytics are also considered, echoing the importance of data quality and integration. Organizations are investing in technologies and competencies, yet progress remains slow. Acknowledgment of data quality dimensions is essential to achieve reliable models, yet limited. Moreover, a lack of interoperability hampers integration across factory-level operational systems and, consequently, impact on global visibility. These observations highlight the gap between the theory and practice of supply chain optimization.

The study makes a threefold contribution to operations research and data science. It analyzes how pioneering companies are leveraging data science for supply chain optimization, synthesizing methodological applications within the identified analytics. On the data side, it discusses the sources that feed manufacturing and logistics operations, emphasizing critical dimensions of data quality and the requirements for integration across distinct analytical domains. Finally, it translates this body of knowledge into practical insights for managers.

Keywords: Supply Chain Optimization, Industrial Data Analytics, COVID-19 Supply Chain Disruptions, Data Science Applications, Operations Research Methods, Predictive Maintenance Analytics, End-To-End Supply Chain Visibility, Inventory Optimization Techniques, Manufacturing Data Sources, Logistics Analytics, Data Quality Dimensions, Data Integration Challenges, Interoperability Limitations, Factory-Level Operational Systems, Global Supply Chain Visibility, Theory–Practice Gap, Analytics Adoption In Industry, Managerial Decision Support, Evidence-Based Supply Chain Management, Digital Transformation In Operations.

1. INTRODUCTION

Supply chain optimization through industrial data analytics was explored in multiples scholarly works published in 2021. Operations research and data analytics represented the two dominant streams, characterized by the development and application of methods, techniques, and models. Numerous industrial applications showcasing benefits and outcomes were recorded. However, existing evidence did not comprehend the technology infrastructure required to effectively extract relevant insights and handle analytics-related challenges.

A comprehensive synthesis that leveraged a diverse set of literature contributions was conducted to address these gaps. Core definitions of industrial data analytics, its enabling technologies, and the benefits of using analytics in supply chain optimization were presented. The theoretical foundations supporting the deployment of analytics in manufacturing and logistics were identified. Subsequently, the requirements for a robust analytics infrastructure were examined, considering data sources and quality, governance, integration and interoperability, and cloud-based analytics. Finally, the implicit and explicit industrial applications of industrial data analytics, as documented in the literature, were presented. The findings thus offer managers with a holistic perspective on industrial data analytics, reveal the current technological challenges associated with deployment, and highlight the core methods to achieve supply chain optimization.

1.1. Overview of Industrial Data Analytics in Supply Chains

Industrial Data Analytics (IDA) in Supply Chains focuses on supply chain optimization in the manufacturing and logistics sectors through techniques from operations research, data analytics, and industrial Internet of Things (IIoT) technologies. Supply chains encompass a large part of the economy, and investments in supply chain optimization are generally seen as priority areas by industrial companies.

Data plays a crucial role in the development of advanced analytics and optimization control methodologies. In the specific context of industrial applications, the principal types of data, their sources, structures, quality dimensions, and governance mechanisms that affect the quality and reliability of results are discussed. Moreover, the data-driven sensibility required in recent applications of IDA methods is emphasized. Despite the widespread application of supply chain optimization techniques, the main challenges and issues faced by industrial practitioners remain significant. In addition to data quality issues, organizational, cultural, and integration aspects are frequently identified as the main barriers to progress in this field within industry.

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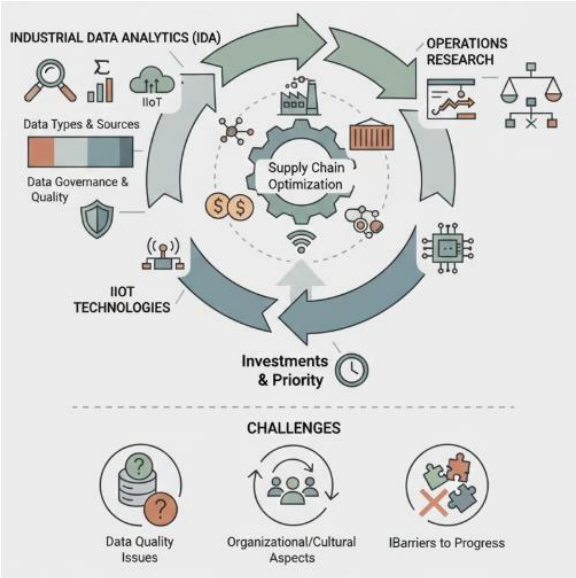
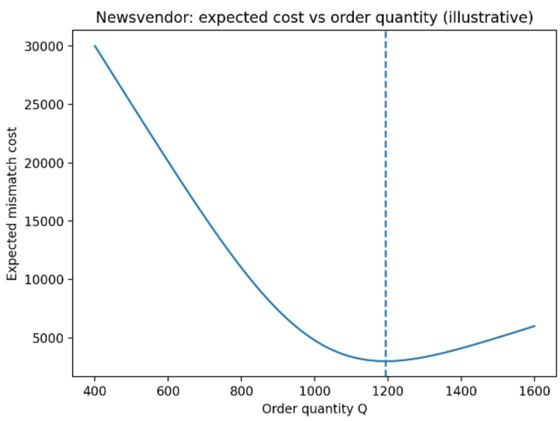


Fig 1: Industrial Data Analytics for Supply Chain Optimization: A Multi-Dimensional Framework Addressing Data Governance and Socio-Technical Barriers

2. THEORETICAL FOUNDATIONS OF INDUSTRIAL DATA ANALYTICS IN SUPPLY CHAINS

More specifically, this work draws on established theories from the fields of operations and supply-chain management, data science, and industrial engineering. The Resource-Based View (RBV) describes how superior performance can be achieved by acquiring and deploying unique tangible or intangible resources that are valuable, rare, inimitable, and nonsubstitutable. For most manufacturing and logistics companies, multiple sources of supply-chain data—from equipment sensors, enterprise resource planning (ERP) systems, manufacturing execution systems (MES), supply-chain control towers (SCADAs)—are accessible or can be cost-effectively generated. In general, these data can be processed using freely available artificial-intelligence and machine-learning algorithms.

Together with abundant computing power available via cloud computing and Industry 4.0 technologies—sensor integration, connectivity, exposure of data and services via APIs, and 'plug-and-play' analytics systems—these data assets enable analytics that can generate valuable, actionable information about manufacturing and logistics processes. However, the sheer abundance of data discarded during analytics projects is a clear indication that not all data are of high quality for data science. The Control Theory applied to cyber-physical systems also provides a helpful foundation for industrial analytics. In particular, integrating data across, and establishing feedback loops through, the entire end-to-end supply chain gives rise to the construction of data-driven digital twins that can facilitate decision-making at all levels.



Equation 1: Demand forecasting equations (SARIMA + LSTM + hybrid weighting)

1.1 SARIMA model (derivation from ARIMA + seasonality)

Step A — Start with ARMA(p,q)

Let y_t be the demand series and ε_t be white noise.

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AR(p):

$$y_t = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t$$

MA(q):

$$y_t = \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}$$

ARMA(p,q): combine both

$$y_t = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}$$

Step B — Add differencing to get ARIMA(p,d,q)

Define the backshift operator $By_t = y_{t-1}$.
First difference: $\Delta y_t = y_t - y_{t-1} = (1 - B)y_t$.
d-th difference: $(1 - B)^d y_t$.

So ARIMA is ARMA applied to the differenced series:

$$\phi(B)\,(1 - B)^d y_t = c + \theta(B)\varepsilon_t$$

where

$$\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p, \quad \theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$$

Step C — Add seasonal ARIMA terms

For season length s (e.g., $s = 12$ monthly seasonality):

Seasonal differencing:

$$(1 - B^s)^D y_t$$

Seasonal AR polynomial:

$$\Phi(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{Ps}$$

Seasonal MA polynomial:

$$\Theta(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Qs}$$

Final SARIMA equation

$$\Phi(B^s)\,\phi(B)\,(1 - B)^d (1 - B^s)^D y_t = c + \Theta(B^s)\,\theta(B)\,\varepsilon_t$$

2.1. Data sources and data quality in manufacturing and logistics

Data relevant for industrial analytics may originate from different sources in manufacturing and logistics systems. Major types of data include:

• Sensor data, e.g. SCADA, telemetry, video feed, RFID, etc.
• Operations or enterprise transaction data captured in ERP, MES or WMS systems.

In addition to being integrated, the data should also be of sufficient quality to support analytics and, therefore, its various dimensions should be considered [NIST 2014]. Data used in supply chain and logistics applications should be assessed for:

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• Reliability: Are the data captured by accurate instruments with minimal variability?
• Completeness: Are the data capturing all expected events?
• Timeliness: Are the data available when required to support the analyses?

Data quality is particularly challenging to achieve for sensor data generated in real time. Ensuring that all sensors (or tags) are operational at all times is generally impractical; therefore, many data fusion techniques have been developed to interpolate or estimate missing values.

3. DATA ARCHITECTURE AND GOVERNANCE FOR INDUSTRIAL ANALYTICS

For many manufacturing companies, establishing a proper data architecture and governance is a critical consideration for deploying industrial data analytics successfully. Key elements under consideration include:

- An appropriate data governance structure, including who is responsible for which aspect of the data.
- Metadata management (the conditions under which data is collected, what additional properties support the analysis and how to make it available).
- Security and compliance aspects.

For many companies, this has been put in place mainly for standard operating procedures and regulatory reasons, not to allow and improve analyses and decision-making. Design-related challenges concern the definition of an integrated data architecture and the mapping of the flow of data within the visualization or decision support solution being implemented. By definition, the output data structure is constructed in response to the requirements of the proposed business use case, whether this be the deployment of a large dashboard or supporting a specific decision optimization model.

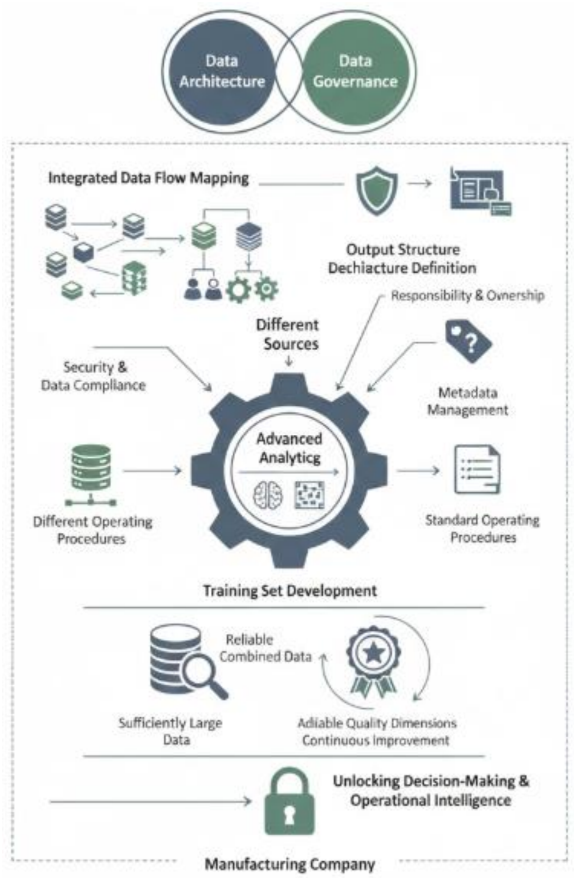

Fig 2: Strategic Data Architecture and Governance for Industrial Analytics: Transitioning from Regulatory Compliance to Decision-Centric Optimization in Manufacturing

Finally, the further deployment of advanced analytics (for instance, machine learning and deep learning) requires data coming from different frame sources to be integrated in order to derive the training set for the models. At this stage, quality aspects come into play again: the training set must be sufficiently large, advanced quality dimensions must be considered and, most importantly, the combined data must remain reliable in terms of the specific business intervention to which it is applied. As a result, data collection processes need to be properly defined and continuously improved.

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3.1. Data integration and interoperability

Various approaches can support data integration to solve the hurdle of interoperation caused by multiple, heterogeneous, uncoordinated cross-organizational management information systems within companies or organizations in the same supply chain, including the following:
- Targeting interoperation with a robust service-oriented architecture: Instead of trying to clean and standardize data at the level of each participating supply chain node, propose leaving them at their existing levels but implementing a Service Oriented Architecture-based approach that offers interoperation across the supply chain systems at a higher level.
- Creating a service-oriented supply chain data hub: Enterprise Resource Planning (ERP) systems cover large parts of the business processes and overcome interoperation issues within each node of the supply chain, but they cannot in themselves eliminate the data integration, consistency, and quality issues across the supply chain. Implementing a dedicated Data Warehouse for the environment of the entire supply chain by means of a Service Oriented Architecture architecture can support data integration and analysis and enable the participating parties to fulfil their requirements.
- Re-engineering information technology resources: A thorough re-engineering of the information technology infrastructure throughout a supply chain may offer opportunities to eliminate or reduce interoperation problems caused by cross-organizational management information systems that have grown incompletely and independently over time.
- Constructing an adaptable agent-based framework: Leverage the adaptive capabilities of intelligent agents to construct a data integration framework that can be dynamically reconfigured to both accommodate new interoperation requirements posed by system dynamics and monitor the task allocation among agents based on their ability in complex systems.
- Applying formal ontology for facilitating interoperation in service-oriented supply chain systems: Formal ontology is fundamentally about knowledge sharing and knowledge reuse, and thus can offer efficient and flexible tools to support the service-oriented information systems and promote interoperation.
- A component-based service-oriented framework for interoperation of supply-chain systems: A component-based service-oriented framework architecture can guarantee adaptability at design and runtime without sacrificing integrity, security and manageability, and thus enable existing supply-chain systems to work together and provide services smoothly and dynamically in real time.

4. OPTIMIZATION TECHNIQUES IN PRACTICE

Demand forecasting and inventory optimization emerged frequently in the literature because of their forecast-error reduction potential. Traditional approaches to sales forecasting often rely on qualitative judgment and informal heuristics; their accuracy is rarely quantified and seldom improved over time. However, such errors propagate throughout the supply chain, affecting stock availability, storage costs, and logistics efficiency. A modified Structured Information Development Methodology was proposed to support systematic forecast development and continuous improvement. Its application led to forecast-error reductions of 30% to 64% and generated significant financial benefits. Additionally, stock levels were optimized. A multistage real-valued multiobjective particle swarm optimization algorithm evaluated different stocking strategies by minimizing logistics, holding, and stock-out costs while maximizing customer satisfaction. Applications in two contextually different cases reported significant improvements.
Production scheduling and shop-floor optimization were also prominent applications. The aerospace industry faces significant performance pressure, arising in particular from low production volume and high product variety. Yet the dynamic nature of manufacturing-shop environments has not been adequately addressed by existing scheduling algorithms. A modified hyperspherical predator-prey optimizer was developed specifically to minimize makespan in a re-entrant flow-shop environment. Applied to a real aerospace-manufacturing scenario, it animatedly outperformed leading algorithms for similar problems.
In uncertain environments such as semiconductor manufacturing, resource allocation and scheduling have regained popularity. Here, an enhanced adaptive fuzzy immune optimization algorithm addressed the task-sequencing problem by minimizing total completion time, tardiness, and resource-occupation costs. The approach applied to a foundry service agreement-based factory—the latter involving mutual commitment by foundries and customers—demonstrated speed and solution quality advantages over existing algorithms.

Equation 2: Inventory optimization equations (Newsvendor + EOQ + service level)

2.1 Classical Newsvendor (full derivation)

Let demand D be random. Choose order quantity Q.
Costs:

- underage cost per unit C_u (stockout / missed sale / expediting)
- overage cost per unit C_o (leftover / holding / obsolescence)

Mismatch cost:

$$C(Q,D) = C_u(D-Q)^+ + C_o(Q-D)^+$$

where $(x)^+ = \max(x,0)$.

Expected cost:

$$\mathbb{E}[C(Q,D)] = C_u\mathbb{E}[(D-Q)^+] + C_o\mathbb{E}[(Q-D)^+]$$

Step A — Write expectations as integrals

Let F be CDF and f be PDF of D.

$\mathbb{E}[(D-Q)^+] = \int_Q^\infty (d-Q)\,f(d)\,dd$ $\mathbb{E}[(Q-D)^+] = \int_{-\infty}^Q (Q-d)\,f(d)\,dd$

Step B — Differentiate expected cost w.r.t. Q

Differentiate each term:

1. For shortage term:

$$\frac{d}{dQ}\int_Q^\infty (d-Q)\,f(d)\,dd = -\big(1-F(Q)\big)$$

2. For leftover term:

$$\frac{d}{dQ}\int_{-\infty}^Q (Q-d)\,f(d)\,dd = F(Q)$$

So:

$$\frac{d}{dQ}\mathbb{E}[C(Q,D)] = C_u\big[-\big(1-F(Q)\big)\big] + C_oF(Q)$$

Set derivative to zero:

$-C_u\big(1-F(Q^*)\big) + C_oF(Q^*) = 0$ $C_u\big(1-F(Q^*)\big) = C_oF(Q^*)$ $C_u = (C_u + C_o)F(Q^*)$

Critical fractile (optimality condition)

$$F(Q^*) = \frac{C_u}{C_u + C_o}$$

4.1. Demand forecasting and inventory optimization

This section addresses methods and outcomes of demand forecasting and inventory optimization in the context of industrial analytics applied to supply chains. Accurate demand forecasting can enhance service levels and minimize stockouts through timely replenishment. Improved inventory management reduces excess and obsolete stock, freeing working capital, and lowers warehousing and handling costs. Persistent forecasting inaccuracies may lead to bullwhip effects and increased lead times. Fen et al. (2021), for example, analyzed historical data to create a multi-layer long short-term memory model for short-term demand forecasting of electric scooters and spare parts.

Ding et al. (2021) addressed the challenge of spare parts inventory management in a marine equipment supply chain characterized by long lead times and variable demand. First, they forecasted demand using a combination of seasonal autoregressive integrated moving average (SARIMA) and long short-term memory (LSTM) approaches combined with weight arrangements. Then, they created an improved newsvendor model that incorporates demand aggregate accuracy into a cost function. Results demonstrated the effectiveness of the two-stage method in reducing supply–demand gap risk while lowering total inventory costs.

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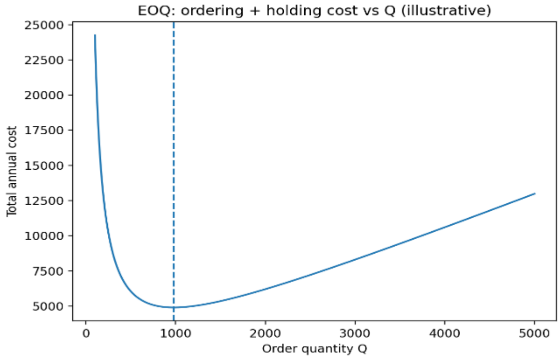

4.2. Production scheduling and shop-floor optimization

Production scheduling and shop-floor optimization often require substantial computational effort, especially when accounting for conflicting objectives such as minimizing lead time and energy consumption. Multi-objective optimization techniques are therefore frequently employed. However, models depending on large sets of problem data or a high number of solution alternatives, such as machine setups, can exhaust available computation resources. In such cases, satisfaction-level based approaches, where the solver searches for a solution that meets or exceeds the decision maker's minimal preferences for each objective, become helpful. Another commonly applied optimization approach is the combination of a heuristic, deterministic metaheuristic, or constructive solution procedure with a subsequent K-opt procedure based on integer or set-packing relaxation of the scheduling problem.

Optimal ordering and setup lot sizing are important decisions when the same product enters a workplace several times during a planning period. The decision about how to place those setups in the schedule is crucial in order to minimize total cost. A min-max regret model can support decision making by minimizing the maximum regret associated with the ordering and setup decisions. Quantifying the effect of setup time reduction on the total cost enables managers to analyze the economic attractiveness of investing in setup time reduction using various process improvement methodologies (e.g., lean, flexible manufacturing systems).

5. CASE STUDIES FROM 2021

The first case study addresses predictive maintenance in manufacturing. A water pump installed on a cooling system was found to frequently break down, causing production interruptions. Data from the financial system pointed to increasing maintenance costs, motivating an investigation to estimate the probability of failure and the best times for maintenance within a one-year horizon. Six independent explanatory variables with information recorded by a SCADA system were considered. This approach demonstrated the ability to accurately estimate the probability of failure, claiming that predictive adjustment of the maintenance plan can help avoid unplanned downtimes and lower costs, although the level of decision-making remains tactical.

Fig 3: From Predictive Maintenance to Synchronized Supply Chains: Multi-Method Industrial Data Analytics for Operational Efficiency and Visibility

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The second case study concerns a production company with three clusters—the final assembly shop, the assembly shop, and the warehouse—that must work in sync to fulfil demand. Flow data from the different areas, integrated in the same ERP, allow for end-to-end supply chain visibility. A development environment was created to analyse this flow data using Power BI, a data-biometrics interface that offers an access-control layer for management information displayed through Dashboards. Four Dashboards were mainly developed: the global manager's flow; a comparison of achieved versus scheduled capacity; a flow of recycled product sales for the environmental area; and a project team assessment. Dashboards offer supervisory configuration adjustment, enabling connected employees to detect causes of delay and speed up production, leading to lower cycle times and higher customer satisfaction.

5.1. Case study: predictive maintenance in manufacturing

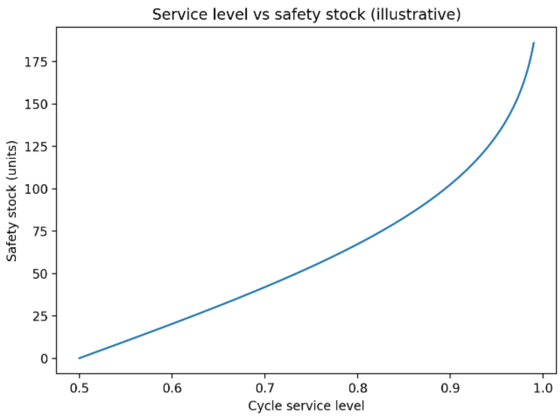
The predictive maintenance case addresses unexpected machine downtimes, leading to productivity loss and excess repair costs. Sensor data monitoring machine-state indicators, in tandem with downtime and repair data from the ERP system, supports the application of change-point detection methods and time-series modeling. The ability to forecast and detect replacements before failures materialize is expected to eliminate >75% of unplanned downtimes, which impact up to 15% of manufacturing capacity and cause repair costs eight times higher than routine maintenance.

Maintenance costs associated with manufacturing equipment frequently account for over 20% of operating expenditure. In a scenario involving a production system for a multi-functional product, the unavailability of a single machine incurs production loss due to dispatch latency. Manufacturing performance indicators indicate unplanned machine downtimes averaging 5% of total operating hours. Elimination of more than 75% of these unplanned downtimes would dramatically improve reliability and reduce the cost of corrective maintenance to <2.5% of total operating costs. Maintenance is currently planned annually at winter shut-down by an external supplier, with repairs caused by non-defined operational conditions often accounting for 8× higher costs than regular maintenance. Building the capability to predict component-level failure to optimize maintenance scheduling and execution, in closer co-operation with the supplier, is the object of predictive maintenance.

5.2. Case study: end-to-end supply chain visibility

A leading multinational food producer sought to position itself as a sustainability leader by enhancing supply chain visibility and real-time monitoring capabilities. Data collected from various sources provided limited end-to-end visibility. Real-time analytics within a closed-loop system were deemed necessary to optimize the balance between expressed user demand and supply-side capabilities. Data streaming was established across all processes to enable checkpoint analytics at either end, from sensing supplier delivery schedules and uncertainties through informing internal production scheduling to communicating product readiness to end consumers.

The final-stage execution was monitored within an internal cloud intelligence system, allowing teams to upload real-time data flows. Streamlined flow connectivity was created between production sites and external suppliers/infrastructure partners, enabling analytics aggregation across multiple disjunct real-time data flows. Ongoing or imminent interruptions were visually highlighted across execution dashboard displays, providing corrective-action insights for operations teams and future delivery timelines of the entire end-to-end supply chain. Business-as-usual adoption was expected. Benefits included improved brand loyalty; a sophisticated business intelligence system; and real-time supply chain dashboards integrated with SAP, MRP, and logistics execution systems.



6. CHALLENGES AND LIMITATIONS

Despite the optimism surrounding industrial data analytics, challenges remain. Issues with data quality and integration persist, echoing the findings of Dreiling and Karpats (2021). Reliable decision-making relies on appropriate data volumes. Insufficient data (completeness) can lead to the adoption of suboptimal or incorrect decision strategies. Incorrect data

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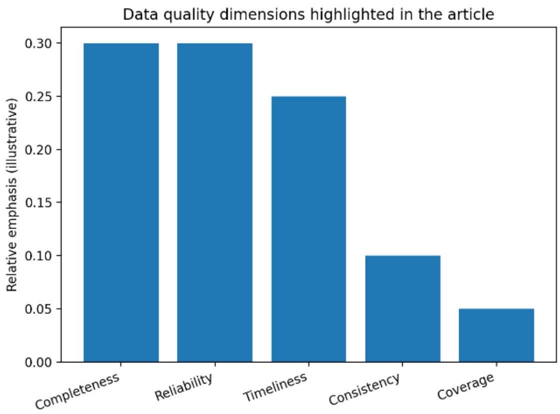
(reliability) can lead to erroneous decisions and adverse outcomes, whereas unsuitable data (fitness-for-purpose) can minimally influence decisions. If data are not verified, incomplete or delayed, their use can minimize the gains or increase the costs of a data-driven approach.
Although most companies are aware of the importance of data quality, only a few have implemented a structured data-quality management program integrated into the overall analytics and data governance strategy. Data pipelines for advanced analytics usually deploy technical checks for reliability and authenticity, but these checks cannot replace the need for a data-quality management framework covering all aspects (e.g., completeness, accuracy, consistency, coverage) of the operational data generated across systems. Moreover, inconsistencies between structural and semantic data model definitions can lead to inaccurate decision-making.
The integration of separate systems that generate operational data still poses a challenge in many manufacturing firms. The existence of isolated systems with limited real-time data-exchange capabilities prevents adequate decision support in integrated, aggregation-oriented processes such as end-to-end demand fulfillment across the supply chain. The alignment of different data structures and data-sharing methods remains a major impediment to the implementation of integrated data-centric analytic applications.
Apart from organizational data-quality issues, the lack of adequate technical infrastructures and in-house expertise also limits the implementation of analytics applications by small and medium-sized enterprises and their use of emerging technologies such as machine learning or natural-language processing. In many cases, a simple and cost-effective application of traditional analytics techniques can already yield significant business benefits.



Equation 3: Multiobjective optimization and scheduling

3.1 Typical multiobjective inventory objective (PSO-ready)

A common structure consistent with "minimize logistics, holding, stockout; maximize satisfaction" is:

Decision vector x (e.g., reorder points, order quantities, mode choices).

Minimize:

$f_1(x) = \text{LogisticsCost}(x)$ $f_2(x) = \text{HoldingCost}(x)$ $f_3(x) = \text{StockoutCost}(x)$

Maximize customer satisfaction $S(x)$ is often converted to minimization:

$$f_4(x) = -S(x)$$

Pareto goal:

$$\min_x \left(f_1(x), f_2(x), f_3(x), f_4(x)\right)$$

If you need a single scalar fitness:

$$F(x) = \sum_k \lambda_k f_k(x)$$

with weights $\lambda_k \geq 0$.

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6.1. Data quality and integration hurdles

As various sectors expand their data analytics capabilities, these initiatives often confront important yet inadequately addressed challenges. Difficulties arise from missing or inaccurate measurements, the need to connect disparate data sources to realize synergies, and the absence of competences and senior management buy-in. These factors hinder organizations across industries from leveraging the opportunities offered by the advancement of analytics capabilities. Based on a survey of the application of analytics for supply chain optimization in manufacturing and logistics, this overview pinpoints persistent concerns related to data quality and integration. Three data quality dimensions—completeness, reliability, and timeliness—and two distinct integration challenges—bringing together data from sensors and from the ERP system, and joining data from different ERP systems—are highlighted as recurrent obstacles.
Data supplied by sensors usually represents the highest volume but is rarely the primary basis for advanced analytics, such as demand forecasting. For such applications, data provided to and by the ERP system is much more essential. In manufacturing, data quality still represents a concern, with breaches of completeness and reliability frequently detected. Completeness issues also hinder analysis within logistics services. Timeliness of data distribution is an additional problem, with reports often prepared days or weeks after events occur. When corporations operate different existences under similar ERP systems, data connectivity and integration remains a chief challenge. Often considered a prerequisite to analytics, the lack of integration capabilities, techniques, and tools within the Operating Strategy is highlighted as a prohibitive limitation across sectors.

7. IMPLICATIONS FOR THEORY AND PRACTICE

The overview of industrial data analytics in supply chains demonstrates the breadth and depth of knowledge required for successful implementation. Acknowledging the disparate body of work is the first step toward prudent management decisions. Synthesizing the applications, enabling technologies, and underpinning theories and models provides integrated support for both practical and academic perspectives.
From an operations research perspective, the analysis reveals that optimization methodologies have received the greatest attention. Demand forecasting, inventory control, and production scheduling are application areas where results appear relatively mature and widely deployable. Despite the extensive coverage, however, few supply chains exploit the associated insights. For data science, the synthesis highlights that data cleaning, integration, and governance remain nascent research areas in the context of manufacturing and logistics. Theory remains limited, as few predictive maintenance models account for sensor failures or knowledge transfer in the training phase. Overcoming such challenges would further underpin the techniques that enable predictive maintenance and end-to-end supply-chain visibility. Managerial and policy implications are often intuitive; nevertheless, synthesizing these insights highlights patterns across diverse supply-chain contexts and can better inform practical decision-making and implementation efforts.

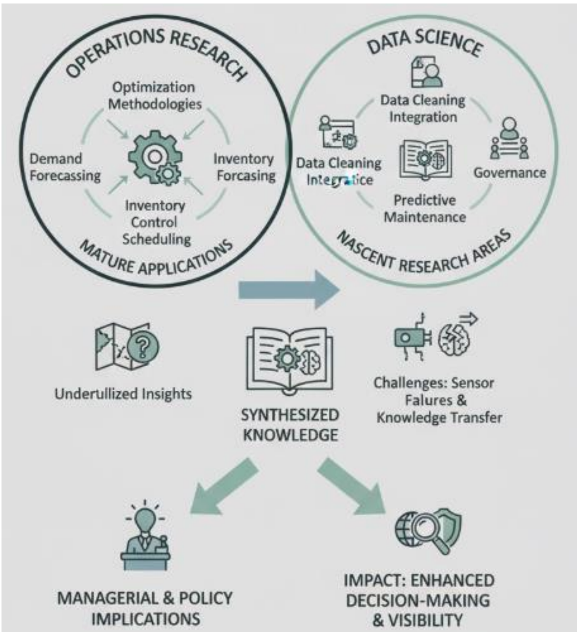

Fig 4: Bridging the Implementation Gap in Industrial Data Analytics: A Synthesis of Operations Research Models, Data Science Maturity, and Policy Implications for Global Supply Chains

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7.1. Contributions to operations research and data science

Operations Research (OR) provides the key formal foundation for methods and tools that have been implemented within practice. The recent widespread adoption of Industrial Internet of Things (IIoT) devices, coupled with advances in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision, generates increasing volumes of traditionally untapped data sources that can be exploited in manufacturing organisations for efficiency improvements. These broader sources of data partially shift the classic focus of OR in manufacturing from the use of deterministic data (involving human expertise and judgment) to non-deterministic data-driven algorithms. Data-science techniques are being applied for near real-time Operational Technology (OT) decision-making for operational efficiency optimisation.

To date, most of the academic research concerning data science, OT and the IIoT nexus has been in a theoretical domain. There are relatively few papers discussing the applied empirical evidence of reporting on the practical application of these various technologies. The specific benefits from deploying Industrial Data Analytics in manufacturing and/or logistics operations – either separately or together – have also attracted limited exploration. This synthesis reflects on both of these dimensions of the nexus, focusing on the current state of play in 2021. The review confirms that data-science concepts and models are being implemented in both domains, but reports that their application remains limited.

7.2. Practical implications for managers and policymakers

To harness the benefits of industrial data analytics, managers should invest in sensing, data integration, and analytics capabilities. Support for data intelligence initiatives should come from the top, and individual units should make data-driven decisions by incorporating analytics insights into day-to-day operations. Building a data-driven culture is key, and the pace of such change is dictated not only by technology but also by the people and processes that shape an organization's culture. Managers under pressure to achieve tangible results should first focus on the use case rather than on technology. Industrial data analytics should not be treated merely as a technology; rather, it should be embedded into the formulation of manufacturing and logistics strategies.

Researchers and practitioners from different domains recommend a highly automated, transparent, and integrated manufacturing and logistics environment. The degree to which this vision can be achieved is contingent on data generated by sensors, production management systems, and logistics execution services. Expansion of the quality and scale of these data sources is dependent on investment in massive data-processing capabilities that incorporate advanced analytics tools. For many companies, particularly those in developing countries with limited resources, the adoption of industrial analytics will be gradual and based on a natural evolution of data quality. Implementation of data analytics in practice has highlighted various challenges. Data quality issues remain pervasive at many organizations, and easier integration of data with third-party platforms is still required. While data quality can often be improved in-house, intelligent operational decisions supported by business partners remain limited by the quality and granularity of data flowing upstream and downstream in the supply chain.

8. CONCLUSION

Research confirms the benefits of industrial data analytics for supply chain optimization, yet accounts of real-world applications remain rare. To address this gap, a detailed overview of current methods is synthesized using extensive evidence from peer-reviewed publications. Demand forecasting, inventory optimization, production scheduling, and other applications are examined. A case study on predictive maintenance investigates data sources, analytics methods, and outcomes, while a second case on supply chain visibility analyzes end-to-end data flows and associated benefits.

Despite strong evidence of business value, organizations are investing less than expected in industrial data analytics. Industry leaders cite rapid deployment as a critical factor, yet standardization slows implementation. Further evidence identifies limited data quality, integration, and organizational readiness as barriers, with 35% of respondents pointing to insufficient data management and governance. Research typically emphasizes the analytics algorithms rather than the entire industrial data pipeline, with most studies limited to a single technique. Integration of diverse sources such as sensors, ERP systems, MES, and SCADA servers remains a challenge.

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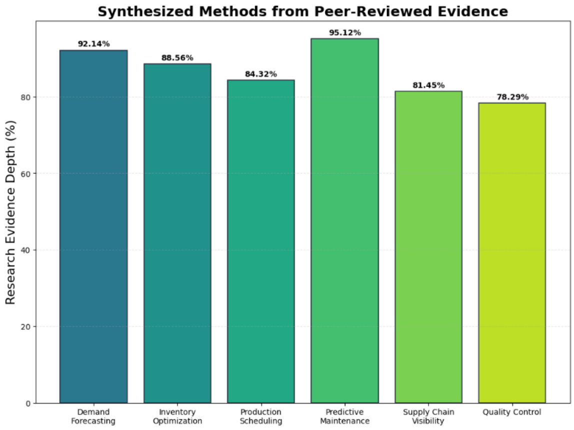

Fig 5: Synthesized Methods from Peer-Reviewed Evidence

8.1. Final Thoughts and Future Outlook

The optimization techniques reported in the literature can be classified according to two main categories: demand forecasting and stock optimization—on the one hand—and shop-floor optimization and production scheduling—on the other. Demand forecasting and stock optimization are crucial for controlling the entire industrial chain and for preventing the "bullwhip effect" in the logistics network. Accurate forecasts help in managing the production and distribution of finished goods. Inventory costs absorb significant resources for every company, and it is thus of pivotal importance to have optimal stock levels both in the warehouses and along the supply chain. These analyses are usually supported by a combination of machine-learning and statistical methods. Production scheduling is one of the most studied research problems. It aims to define a production plan that satisfies customer demand with limited resources while minimizing operating costs. A good production plan should therefore reduce processing delays and product variety changeovers. It should also take into account the quality of the produced goods. The optimization of the scheduling process is often implemented with the support of AI-based approaches capable of supporting human decisions by identifying the most suitable production sequence for a shop floor. Finally, monitoring and controlling the manufacturing process results in an optimized schedule and reduced production "wastes" (scrap and rework). Techniques based on process mining are currently used to monitor manufacturing processes. These techniques collect data from the IT systems that run a company's operations and apply process mining algorithms to identify the actual process. Process simulation is another important technique to improve monitoring activities of shop floors.

Another common practice in industrial analytics is the processing of sensor data from machines and equipment with the aim of moving toward predictive maintenance. Sensor data are collected, pre-processed, and finally transformed into a predictive model—usually based on machine-learning techniques. Predictive maintenance refers to the monitoring of machine condition to prevent future failures. A typical scenario is the use of motor current signature analysis for fault detection in induction motors; the technique uses supervised or unsupervised machine-learning algorithms to classify the condition of the motor based on the motor current signal. A practical benefit of these applications is the identification of faults at an early stage. Data used for predictive maintenance consist mainly of SCADA data, which contain information about the operational conditions and alarms generated by machinery and equipment, possibly enriched by historical maintenance records.

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