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A DATA-DRIVEN FRAMEWORK FOR INCREMENTAL SUPPLY CHAIN OPTIMIZATION

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Purpose: This paper develops an incremental supply chain modeling framework using Big Data and Data Science methods to enhance decision-making, adaptability, and operational efficiency. By integrating advanced analytics, it offers a scalable approach to optimize real-world supply chains.
Design/methodology/approach: The model was developed utilizing the Design Science Research (DSR) methodology, ensuring a structured and rigorous approach to its creation and validation. I propose a four-phase approach—data collection, analysis, decision-making, and model enrichment—combining theoretical insights from supply chain modeling with practical Data Science methods. This iterative method was tested on a retail supply chain to validate its utility.
Findings: The results show that incremental modeling enhances adaptability by enabling quick reconfiguration amid changing conditions and improves decision-making through analytics integration. Each iteration reduces both the time and cost of technical implementation.
Research limitations/implications: Because the study focuses on one retail supply chain, the findings may not be fully generalizable. Future research could examine the framework in other sectors or explore its scalability to more complex supply chains.
Practical implications: By leveraging Big Data and Data Science, the framework provides deeper supply chain visibility, refined resource allocation, and cost reduction. Real-time insights also strengthen alignment between supply chain strategy and operational execution.
Social implications: More efficient resource use and lower waste levels support sustainable supply chain practices. These insights can guide corporate policies on environmental and social responsibility, while promoting data-driven decision-making.
Originality/value: This paper presents an innovative incremental model integrating Big Data and Data Science methods. It aids managers, analysts, and policymakers in boosting operational efficiency within dynamic environments. Moreover, it accounts for the resources and skills required at each stage of supply chain modeling.
Keywords: Supply Chain Modeling, Big Data Analytics, Data Science Applications, Supply Chain Optimization, Decision-Making.
Category of the paper: framework development.

1. Introduction

1.1. Research questions

A detailed analysis of competition for customers in the market highlights continuous product improvement. A thorough analysis of the literature was conducted on Big Data (BD) technology in supply chains (SC) and the methods of SC modeling. Insights gained from the literature were supplemented with business experts interviews. Previous work on the proposed method have been described in the author's earlier publication (Górtowski, Lewańska, 2019).

The literature review focused on several key aspects of SC modeling, including weaknesses in current methods and the use of BD in these models. Based on the above motivations, the following research questions were formulated:

Q1: Who should be involved in creating the supply chain model? What competencies are required, and what roles are necessary for building such a model?

Q2: What does an iteration of supply chain modeling look like?

Q3: What Data Science methods can support supply chain modeling?

1.2. Methodology

To explore and systematically organize the challenges associated with implementing SC model in automated data analysis, the Design Science Research method was selected due to its widespread recognition and justification in the information systems literature (Hevner, 2004).

The study builds on existing definitions and frameworks for DS-supported business data analysis, which serve as the Knowledge Base, forming the theoretical foundation of the research and methodology. Simultaneously, evolving business needs and trends define the Business Environment, ensuring practical relevance and alignment with real-world applications, particularly in integrating modeling solutions into corporate infrastructures.

Key artifacts identified in this study include the SC modeling method architecture, a DS-supported data analysis model, and a working prototype of SC model. These artifacts are iteratively developed, evaluated, and refined through the Rigor and Relevance Cycles. The Rigor Cycle ensures the refinement of artifacts based on insights from the Knowledge Base, incorporating existing DS applications, data visualization automation, and best practices. The Relevance Cycle, guarantees that the study addresses practical business challenges through user evaluations and real-world testing, leading to continuous improvements.

At the core of this process, the Design Cycle bridges theoretical foundations (Rigor Cycle) with practical applications (Relevance Cycle) by facilitating the iterative development, evaluation, and enhancement of system modules and resources. Ultimately, the study contributes back to the Knowledge Base by defining requirements for automated business data analysis and validating the proposed solutions through empirical testing. A summary of the Design Science Research components and their application is presented in Table (Table 1).

Table 1.
The Design Science method components and its application

Component	Definition	Application in Study
Knowledge Base	Fundamental principles established through existing scholarly studies.	Existing Data Science applications, supply chain optimization frameworks, and best practices. The study also contributes to the Knowledge Base by defining requirements for incremental supply chain modeling.
Business Environment	Practical industry dynamics, emerging trends, and organizational requirements.	Trends in supply chain management, particularly in integrating Data Science and Big Data solutions into corporate decision-making.
Artifact	Deliverables generated from the research, including conceptual models, analytical frameworks, and practical tools.	Proposed incremental supply chain modeling framework, including the methodology, data-driven decision-making approach, and a prototype application.
Rigor Cycle	Continuous improvement driven by established theoretical insights and past research findings.	Iterative development of the framework based on prior research and best practices, refining methodologies for incremental supply chain modeling.
Relevance Cycle	Ongoing adaptation informed by industry developments and stakeholder feedback.	System evaluation and adaptation based on user feedback and real-world supply chain scenarios.
Design Cycle	The fundamental cycle of developing, testing, and enhancing conceptual and practical components.	Development, evaluation, and refinement of framework components, ensuring practical applicability in supply chain optimization.

Source: own elaboration.

2. Literature review

This section discusses the evolution of SC modeling, focusing on the integration of advanced analytics and modeling approaches. It highlights the role of BD in addressing SC challenges and examines key Data Science (DS) methods applied in the field of SC improvement. Additionally, it identifies gaps in the existing literature that this study aims to address.

2.1. Supply Chain Modeling Methods

In the literature, SC models are often categorized through various methods, including mathematical models, simulation models, and hybrid models and by their treatment of randomness, i.e., deterministic versus stochastic (Wofuru-Nyenke et al., 2023). Researchers use various modeling methods to address challenges in SC management, including sustainability, efficiency, resilience, and uncertainty. The choice of modeling approach depends on the specific problem and data characteristics, with simulation and hybrid models gaining popularity due to their ability to handle uncertain and stochastic data (Wofuru-Nyenke et al., 2023).

These methods provide relatively safe and cost-effective means of exploring potential solutions, especially when real-world testing is impractical or costly.

Simulation tools, including discrete-event simulation and agent-based modeling, are employed to enhance SC resilience and manage disruptions (Benjamin Korder et al., 2024). Data envelopment analysis (DEA) is used to measure retail SC efficiency, with approaches such as standard DEA models, efficiency decomposition models, network models, and game-theory-based models (Andrejić, 2023). System dynamics modeling is employed to create cause-effect curves and improve SC performance, particularly focusing on agility and flexibility indicators (Liu et al., 2023). Uncertainty analysis and optimization modeling (UAO) are increasingly applied to SC management under uncertain conditions, with decision-making being a common application area (Chen et al., 2023).

Industry 4.0 has spurred innovations in SC optimization, introducing new modeling conditions, inputs, decisions, and algorithms (Xu et al., 2024). The paper identifies promising avenues for future research, such as self-adaptive models and uncertainty reduction techniques in SC networks.

Digital twin technology is increasingly applied across various sectors, enabling more effective SC management in areas such as infrastructure, manufacturing, and agriculture (Hirata et al., 2024). Additionally, by integrating machine learning methods, such as topic modeling, Hirata et al. identify key areas of innovation, including the role of AI, blockchain, and the physical internet, which collectively redefine the scope and capabilities of SC processes. This underscores the growing need for data-driven approaches in dynamic environments.

2.2. The Role of Big Data Analytics in Supply Chains

Business analytics plays a key role in enabling continuous improvement within Industry 4.0. As (Wolniak, 2024) indicates, advanced analytical tools—such as predictive modeling and real-time data visualization—enhance operational efficiency and improve the quality of supply chain management. The integration of these technologies allows organizations to identify inefficiencies, forecast potential issues, and respond swiftly to changing market conditions (Wolniak, Grebski, 2023; Wolniak, 2024).

Big Data Analytics (BDA) is crucial for enhancing supply chain management and decision-making. It improves strategic purchasing and supply management decisions—especially when combined with strong absorptive capacity (Patrucco et al., 2023)—and enables organizations to optimize operations, make informed decisions, and improve forecasting accuracy across the supply chain (Agrawal, 2024). Furthermore, BDA contributes to decarbonization efforts by fostering sustainable growth and innovativeness (Kumar et al., 2023). Despite its slower adoption compared to other business areas, its integration is increasingly important for enhancing operational efficiency, reducing costs, and meeting customer demands in today's dynamic market landscape (Patrucco et al., 2023; Agrawal, 2024).

In response to uncertain business climates, environmental challenges, and regulatory pressures, organizations are adopting sustainable supply chains supported by advanced data analytics. This multi-layered, cloud-based approach integrates business process modeling, machine learning, and visualization to enable intelligent, insight-driven decision-making. Such methodologies have been successfully applied in supplier quality management to improve supply chain performance and achieve sustainability goals (Stefanović et al., 2025). Additionally, when powered by artificial intelligence, BDA significantly influences green supply chain collaboration, sustainable manufacturing, and environmental process integration (Rashid et al., 2024), ultimately contributing to sustainable performance and competitive advantage in supply chains (Kumar et al., 2024; Rashid et al., 2024).

Data Science (DS) and BDA are increasingly applied in supply chain modeling to enhance efficiency, resilience, and sustainability (Jahani et al., 2023). These technologies support data-driven decision-making across various processes, from targeted marketing and inventory optimization to supplier risk assessment (Sanders, 2016). In agriculture supply chains, emerging technologies like IoT, blockchain, and big data are driving digital transformation and sustainability (Kamble et al., 2020). Applications of predictive analytics—such as time-series forecasting, clustering, neural networks, and support vector machines—are proving valuable for demand forecasting in supply chains (Seyedan, Mafakheri, 2020). However, further research is needed on BDA applications in closed-loop supply chains, as robust implementation requires careful planning and investment (Kamble et al., 2019; Sanders, 2016).

Machine learning (ML) has become increasingly important in addressing complex decision-making challenges in supply chain management (Babai et al., 2024). Recent applications have focused on demand forecasting, inventory management, and transportation. For example, ML algorithms like Random Forest and Artificial Neural Networks have shown high accuracy in predicting feedstock yield, productivity, and quality in biodiesel supply chains (Kim et al., 2024). Moreover, ML and AI have demonstrated excellent performance in fraud detection (Lokanan, Maddhesia, 2024), while IoT-based frameworks using ensemble ML methods have improved demand prediction accuracy in cross-border e-commerce (Wang, 2024). Deep learning architectures, such as LSTM and CNN models, have also shown promise in predicting late orders and classifying supply chain risks (Bassiouni et al., 2024), and data-driven robust optimization techniques are being employed to design sustainable cold supply chains for perishable products by integrating ML to construct uncertainty sets from historical data (Arabsheybani et al., 2024).

2.3. Gaps in Existing Literature

Lack of comprehensive frameworks that integrate Industry 4.0 tools like IoT, blockchain, and artificial intelligence into SC model. The article highlights the need for a holistic approach to align advanced technologies with sustainability objectives. General frameworks may lack specificity for certain industries, leaving a gap in tailored solutions for sectors like manufacturing, services, retail or agri-food.

Limited focus on the role of human factors, such as training, collaboration, and resistance to change, in the successful implementation of SC modelling. Research on the importance of aligning workforce development with technological BD advancements is limited.

The dynamic nature of modern SCs, driven by frequent changes and the need for real-time decision-making, necessitates the adoption of advanced technologies. However, existing models often lack the ability to quickly reconfigure in response to shifting market conditions or unforeseen disruptions. This gap highlights the urgent need for innovative methods and tools that enable rapid adaptation and ensure SC resilience.

The diversity of SC modeling methods reflects the complexity and dynamic nature of SC systems. While traditional methods offer foundational approaches, the integration of BD, DS, and incremental strategies addresses modern challenges, enabling organizations to adapt to real-time changes and optimize their operations. The next section will elaborate on how these methods are incorporated into the proposed incremental SC modeling framework.

3. Adapting Supply Chain Modeling for Business Applications

The method of incremental modeling for supply chains is based on authors' experience in implementing the model within a retail supply chain. In today's rapidly changing economic environment, it is essential that the tools, models, and systems especially those supporting decision-making are integrated into the enterprise system and can quickly adapt to evolving conditions. Our approach not only embeds the model within the organizational framework but also clearly defines the roles and responsibilities of the involved team members.

This integration allows the model to respond effectively to shifts in market dynamics, ensuring that analytical accuracy is maintained despite the high costs and lengthy development times associated with traditional simulation models. The model's adaptability is further supported by a robust data environment that provides continuous access to up-to-date information, processing tools, and business insights. These adaptive elements and their operational specifics are further detailed in Section 4.

3.1. Supply Chain Modeling Assumptions

The model operates within a specific environment and must align with the enterprise's requirements. At the same time, it should deliver benefits that outweigh the costs of its construction and maintenance. The primary purpose of the model is to understand and describe dependencies within the (SC) and to integrate the results into decision-making systems.

This becomes particularly important when multiple stakeholders are involved in the modeling process, where one critical requirement is the ability to reconfigure the model promptly.

It is important to note that SC modeling extends beyond the creation of a mathematical representation. From an organizational perspective, it is a multi-stage task involving various units and individuals with diverse competencies. Figure 1 presents the simplified phases of a traditional modeling process.

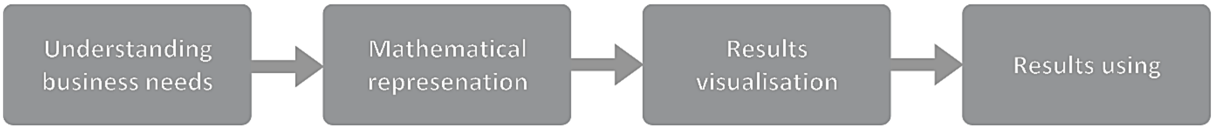

Figure 1. Stages of creating a classic model.

Source: Own study.

Business needs evolve rapidly, making it impossible to define all relevant questions in advance. As these needs grow, greater precision or new areas may be required, and iterative feedback is necessary due to inevitable information transfer errors.

A mathematical representation links the supply chain's information with data—integrating sources, processes, and nodes via algorithms. Results must be clearly visualized to support decision-making and ensure a return on investment (see Figure 2), yielding benefits like risk avoidance, cost reduction, sales growth, and margin optimization.

However, this process has limitations, including unclear role definitions and missing steps such as data acquisition and governance. Moreover, shorter times to actionable results increase information value. Considering these challenges and our experience with similar models, the method was developed.

3.2. Method Phases

Building on the observations and experience gained from implementing similar models, the incremental modeling method was developed. Figure 2 illustrates the relationship between the environment and the SC model. The environment provides data describing SC objects, processes, performance measures, and KPIs, as well as data on external relationships.

The method consists of four main phases, each requiring different tools, knowledge, skills, human resources, and organizational input. These phases are numbered 1-4 in Figure 2. For each phase, a specific outcome is defined as its product. Letters (A–F) denote relationships between the phases and the environment. For instance, (A) represents the resources the environment provides to the model, while (D) indicates the model's influence on decision-making and, consequently, the SC.

3.3. Data Collection

Data collection forms the foundation of the incremental supply chain modeling framework. Data is gathered from diverse channel- both internal (e.g., transactional databases, ERP systems, IoT sensor data, master records) and external (e.g., public databases, government reports, social media, partner data) to capture a comprehensive view of supply chain dynamics. Supplementary datasets such as weather, internet traffic, and social media trends further enrich the model by providing both historical and real-time information for robust decision-making.

To ensure data integrity, potential errors and biases are systematically identified and corrected. Common issues like missing values, duplicate records, and inconsistent formats are closely monitored, while systematic biases (e.g., selection or confirmation bias) are assessed using statistical analyses and visualization techniques, such as distribution charts and correlation matrices. These measures ensure that the dataset accurately reflects underlying processes without distortion.

As shown in Figure 2, the first phase (Step 1) involves gathering, organizing, and verifying data quality, as well as defining performance measures and KPIs. Key tasks include:

- Collecting data in the warehouse.
- Keeping records updated.
- Enhancing data quality.
- Acquiring new datasets.

Additionally, the business environment provides essential knowledge to define measurement criteria, linking data origins to KPIs so that analysts can evaluate specific locations, participants, and processes. At this stage, a well-structured data warehouse is established for further analysis, with the flexibility to incorporate new datasets or performance measures as needed.

Rigorous quality control procedures are embedded throughout the process. This includes comprehensive cleaning routines (e.g., removing duplicates, imputing missing values), automated validation checks within the ETL processes, and periodic audits by domain experts. Detailed documentation of these procedures ensures transparency and reproducibility, reinforcing the credibility of subsequent analyses.

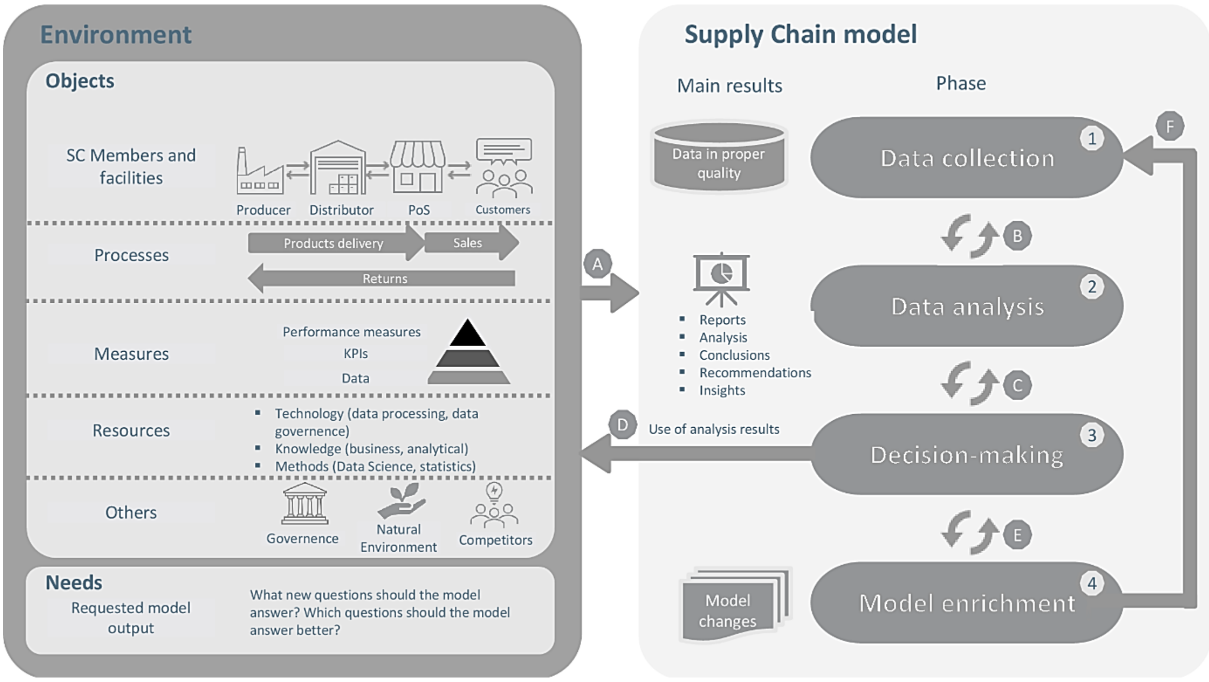

Figure 2. The relationship between the environment and the supply chain model.

Source: Own study.

3.4. Data Analysis

The second phase, data analysis (Step 2), lies at the core of the incremental modeling method. Its purpose is to generate insights, recommendations, and conclusions about the SC based on the collected data. A detailed flow of this phase is shown in figure (Figure 3).

Inputs to this phase include the data model (with connections, KPIs, and performance measures) and the information needs of the environment, often framed as business questions. These questions guide the analysis and define its expected outcomes, such as:

- optimization of indicator values,
- selection of relevant measures and KPIs,
- improved understanding of SC operations,
- prioritization of measures.

The analysis may also uncover insights beyond its scope, influencing future decision-making.

In Step 2.1, analysts interpret business questions and select a corresponding dataset, including fact tables and dimensions. These are translated into specific KPIs and target variables, forming the foundation for applying DS methods in Step 2.2. Various methods are utilized in this phase:

- Factor analysis identifies interdependent variables and reduces dimensionality, isolating key factors that influence outcomes.

- Classification and clustering group similar objects, such as customers or production units, revealing underlying structures. These clusters may evolve with each model iteration, dynamically adapting to changing environments.
- Outlier detection identifies anomalies that positively or negatively affect outcomes, highlighting areas for further investigation.
- The final products of this phase are reports and dashboards (Step 2.3) that present results in a clear and coherent manner. Effective visualization and storytelling techniques enhance the interpretability of these findings, which are then passed to the next phase.

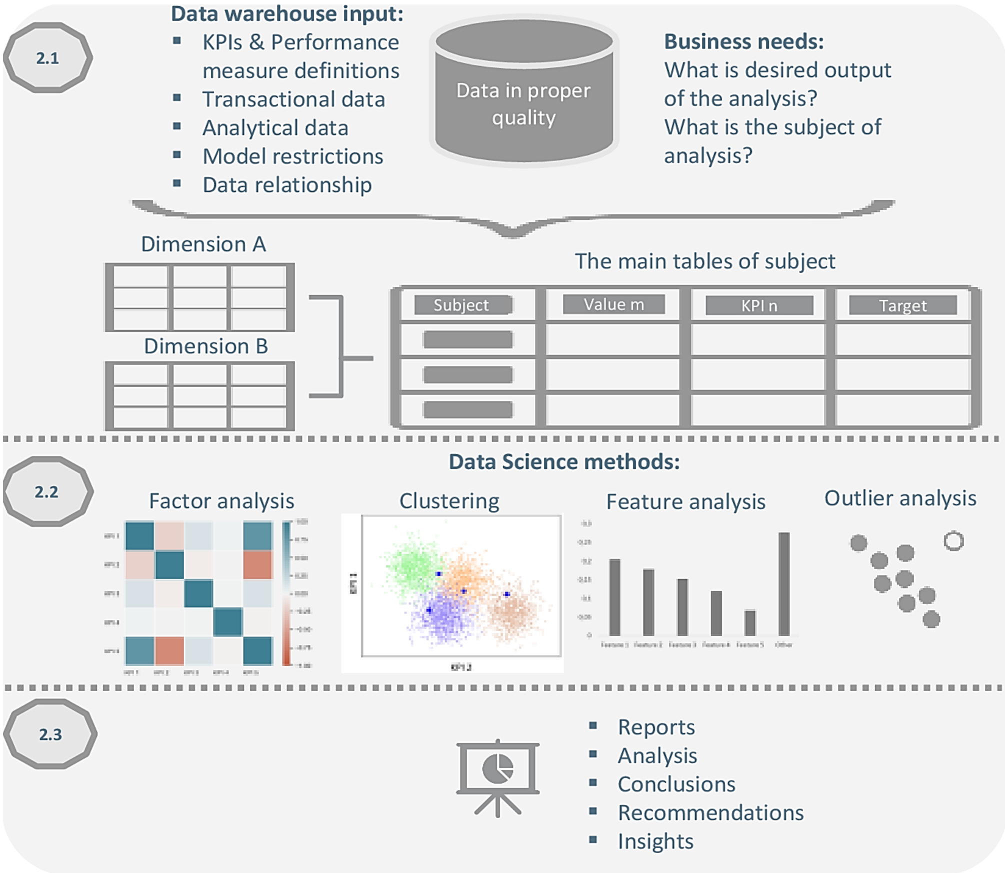

Figure 3. Data analysis phase.

Source: Own study.

3.5. Decision-Making

Phase 3 begins with the acceptance and validation of analytical results. Given real-world business constraints, constructing a second model for validation is often impractical. Instead, assessment relies on:

- expert evaluation of the results,
- sensitivity testing (e.g., reducing random data to observe impact),
- logical consistency (e.g., avoiding illogical dependencies or negative values).

Validated results inform decisions to refine the SC (Step D) and generate new questions for future iterations (Step E). The model's value is determined by its ability to deliver benefits that exceed its development costs.

Good data visualization facilitates understanding among decision-makers, bridging technical analyses and business insights. The model adapts to changing conditions through self-configuration, updating clusters, features, and outliers based on new data patterns.

3.6. Model Enrichment

Phase 4 focuses on refining the model to address new questions or challenges identified in the previous phase. Possible directions include:

- introducing new analytical methods,
- incorporating business-driven modifications,
- modeling additional elements,
- exploring alternative scenarios or business methods.

This phase concludes with Step F, marking the completion of the current iteration. Objectives may be achieved, deferred, or revised for the next cycle. Subsequent iterations typically run more efficiently, leveraging prior work and aligning with the learning curve.

4. Applying Data Science to Supply Chains Modeling

The DS methods introduced in phase (2.2) represent only a fraction of their potential in supply chain applications. Their full range can be expanded in future iterations as analysts gain expertise, the knowledge base evolves, and new analytical needs emerge. Analysts can leverage specialized tools and libraries in Python, R, Scala, C++, and Julia to implement these methods efficiently without building solutions from scratch.

Framework employs advanced DS techniques tailored for dynamic environments. For instance, clustering groups similar entities (e.g., customers, suppliers, distribution points) based on shared characteristics, while dimensionality reduction methods like PCA extract key performance indicators, allowing decision makers to focus on critical metrics. Regression analysis models relationships between variables to forecast trends such as demand fluctuations and transportation costs, enabling proactive decision-making.

Additional methods include outlier detection to identify anomalies (e.g., irregular delays, unexpected cost increases) and optimization algorithms to solve complex problems like route planning and inventory management. Classification techniques support resource allocation by categorizing SC elements, and scenario simulations test resilience by modeling hypothetical disruptions. Together, these methods form a robust toolkit that effectively addresses the complexities of modern SCs.

Table 2.
Exemplary Applications of Data Science Methods in Supply Chains

Method Group	Algorithms	Application in the Model
Classification	SVM, nearest neighbors, random forest, neural network	Assigning products and stores to predefined groups
Regression	SVR, nearest neighbors, random forest	Forecasting; defining a function that describes changes in the values of model components
Clustering	K-Means, spectral clustering, mean-shift	Identifying new customer or point-of-sale (POS) segments based on characteristics
Reduction of Dimensionality	PCA, K-Means, feature selection, non-negative matrix factorization	Reducing redundant dimensions; selecting relevant performance measures; identifying features significant for analysis
Model Selection	Grid search, cross-validation, metrics	Choosing the best model from a set of options; optimizing model parameters
Optimization	Nonlinear least-squares, curve fitting, root-finding algorithms	Finding quasi-optimal solutions; supply chain parameterization
Interpolation	Multivariate data interpolation, radial basis function	Improving data quality

Source: Own study.

Table (Table 2) presents a selection of method groups, sample algorithms, and their potential applications within a model. It is important to note that this list is not exhaustive; the specific methods and their applications will depend on the unique requirements. Similarly, the examples provided here are illustrative and may not capture the full scope of potential uses.

5. Conclusions

Observations made during the creation of such a model highlight several critical areas essential for its successful implementation. These include the tools and technologies used, the required skills, human resources, and methods derived from the knowledge base. Table 3 provides a detailed breakdown of these areas across the different phases of the method. The analysis of the table reveals the distinction between technical and business-oriented phases, each requiring different tools and human resources. Data analysis emerges as the pivotal stage, where technical knowledge is translated into actionable business insights.

While SC modeling is not a new concept, it has yet to fully integrate BD technology and DS methods into a cohesive approach. Modern SCs increasingly recognize the potential of these methods, as evidenced by their growing application in both business and research. The widespread adoption of DS underscores its immense potential to transform SC operations.

The development of this method relies on the integration of DS methods and their incorporation into decision-making systems. Achieving this requires not only the right technological infrastructure but also adequately skilled human resources. Dividing the modeling process into distinct phases, each with its unique skill set, ensures the effective allocation of specialized resources.

The proposed incremental SC modeling approach has been successfully implemented in a large retail enterprise, showcasing its practical value in an industry characterized by rapid market shifts and intense competition. By integrating new datasets and analytical methods on an iterative basis, the company can adapt swiftly to changes such as fluctuating demand, evolving consumer preferences, or emerging logistical constraints. Rather than having to rebuild the entire model after each adjustment, the incremental framework allows analysts and decision-makers to incorporate fresh insights into existing structures, significantly reducing both time and cost. This flexibility ensures that the model remains resilient and up to date, even as external factors shift.

Table 3.
Summary of Resources Used in Each Phase

Phase	Tools and Technologies	Skills	Human Resources	Knowledge Base
Data Collection	Data Warehouse; ETL tools, data extraction, data parsers	Data security; Effective large-scale data processing; Data quality improvements; Data mapping	BI architect team; Data governance team; Data management team; Personnel responsible for personal data processing; Legal team	Data manipulation; Data processing methods; Data verification methods
Data Analysis	BI Tools; IDE for programming (e.g., Python, R, Scala)	Soft skills — communicating business requirements, analysis goals, and business relations; Analytical — data warehouse usage; Mathematical; Data visualization	Data Scientists; Data Analysts; Business area owners; Key users knowledgeable about business processes	Basic statistical methods; Data Science methods; AI; Model optimization methods; Supply chain modeling methods; Business process descriptions
Decision-Making	BI tools; Results presentation	Business decision-making; Inference; Results interpretation	Business owners; Data Analysts; Managers	Storytelling; Visualization techniques
Model Enrichment	Checklist; Data Warehouse	Model validation; Control of data flows; Model verification	Data Scientists; Data Analysts; Business area owners; Key business users	Model sensitivity assessment methods; Modeling methods

Source: Own study.

A key strength of this method lies in its emphasis on interdisciplinary competencies. The modeling team typically comprises data scientists, information technology specialists, and supply chain managers who collaborate to translate technical outputs into actionable business strategies. Such synergy leverages the deep domain knowledge of operational staff alongside the advanced analytical skills of data professionals. In addition, the approach recognizes the organizational dimensions crucial to successful implementation: clear communication channels, well-defined decision-making processes, and supportive leadership structures are considered integral to sustaining iterative improvements. By proactively involving a broad range of stakeholders from different departments, the model not only addresses technical and data-related challenges but also aligns with the strategic and organizational realities of the enterprise. This holistic perspective ensures that the incremental SC modeling framework is both technically robust and readily adaptable to the dynamic conditions of the retail sector.

Future research will focus on expanding the model's applicability, integrating risk management strategies, and providing quantitative performance benchmarks to validate its effectiveness.

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