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Big Data AI for Smart Supply Chain Risk Forecasting

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Abstract

Unprecedented disruptions, such as natural disasters, pandemics, geopolitical conflicts, and other unanticipated scenarios, impose significant challenges on global supply chains. Supply chain disruption prediction is a crucial area of supply chain management, enabling proactive risk management and resilient operations. AI-driven big-data platforms integrating heterogeneous data from multiple domains can help identify such unexpected disruptions. Data ecosystems consist of the various sources needed for the prediction task, along with processes and technologies for integration and data quality assurance. Data quality, privacy protection, and governance are often crucial factors, especially when dealing with personal, sensitive, or regulated information. Multiple modeling approaches—time-series analysis, anomaly detection, graph-based methods, and network analytics—can be operated in parallel and combined. Scope and prediction quality can depend on deployment scenarios, for example, in the procurement, supplier, transportation, and logistics domains.

The AI-driven platforms enable the early, intelligent prediction of disruptive events. Timeliness remains a key requirement, given the speed of many supply chain processes. Predictive performance can be benchmarked using dedicated metrics, including quality and speed. Jeremy Haefner's vision of a collaborative, co-designed platform should also be applied to validation; industry partners should provide test data from private data lakes for calibration and subsequent progress testing.

Keywords: Supply Chains, Disruption Prediction, Risk Management, Resilience, Big Data, AI Platforms, Data Ecosystems, Data Integration, Data Quality, Data Governance, Privacy Protection, Time Series, Anomaly Detection, Graph Analytics, Network Analysis, Procurement, Transportation, Logistics, Predictive Models, Performance Metrics.

1. Introduction

The global supply chain network, after decades of optimization for efficiency, cost minimization, and sheer speed, is now becoming more complex because of both external and

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internal requests. Nobody could forecast the events mentioned earlier, and companies are struggling to operate it. Over the past few years the world has experienced different kinds of supply chain disruptions such as various natural disasters in Japan, China, and the Philippines, the Norwegian oil drilling fire incident, the political crisis in Egypt and Libya, ash cloud in Europe, and the spread of H1N1 flu virus. Big Data Platforms dedicated to supply chain disruption prediction have been developed by leading global tech firms, using data from multiple sources combined with analytics capabilities.

Corporate supply chain stakeholders such as logistics and transportation, supplier management and risk analysis, procurement, and inventory management also require early warning services about disruptive events that could have a significant impact on their businesses. Various new technologies such as Cloud, Big Data, Internet of Things, and Artificial Intelligence will be further developed and combined to support intelligent prediction capabilities in next-generation supply chain disruption prediction systems. Data ecosystems for supply chain disruption prediction are being deployed in several Asia-Pacific regions. These ecosystems support the collection of supply chain-related data such as global meteorological data, global seismic risk data, logistics-related data, and shipping sea route risk assessment data.

2. Background and Foundations

Supply chains have become increasingly vulnerable to disruptions caused by a variety of events, including both natural and man-made disasters. These disruptions can encumber timely delivery of goods and logistics services, disturb demand and supply components, and ultimately raise costs. Disruption risk can often be mitigated by initiating predications much before the actual failures occur. A data ecosystem approach is essential for the predictions, especially for costly disruptions that fit a clear pattern in the temporal and spatial dimensions. Recent research shows that such costly disruptions can often be predicted up to 60 days ahead using only macroeconomic time series data. The ability to discover these costly trends and anomalies affecting supply networks enables organizations to manage their operations better and thereby save 10–15 percent.

A data ecosystem for prediction of supply chain disruption embedded within smart data platform architectures provides all necessary capabilities, including data sourcing, quality, and governance. Particularly, provisions for advanced analytics such as statistical packages for time series and anomaly detection, graph and network analytics, scalable compute and storage capabilities with outlier detection in temporal data and temporal data mining functions are

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critical. Prediction use cases cover smart procurement and supplier risk management as well as transportation and logistics optimization.

2.1. Supply Chain Disruptions: Patterns and Impacts

An important characteristic of supply chains is their vulnerability to disruptive events, either natural (fires, floods, storms) or man-made (strikes, political unrest, terrorism). Earthquakes and tsunamis are particularly impactful because they are infrequent but generate heavy damage. Disruption risk is only modestly reduced by purchasing insurance since it does not eliminate supply chain dependencies. These can only be addressed by changing supplier locations and via inventory buffers.

Supply chain disruptions have their consequences. When the direct impact is large, secondary effects can be just as important. Since a supply chain can be understood as a network, the review process needs to consider not only the center with direct risk; the other parts of the network have to be analyzed too. Built networks are not static; they evolve over time and one can distinguish three stages in the life cycle of a supply chain: the embryonic stage, standardization and modularization. In this last phase, the structural dependence among the supplier network and the assemblers or brand owners are mostly established, and the strategic capital investments will have been made.

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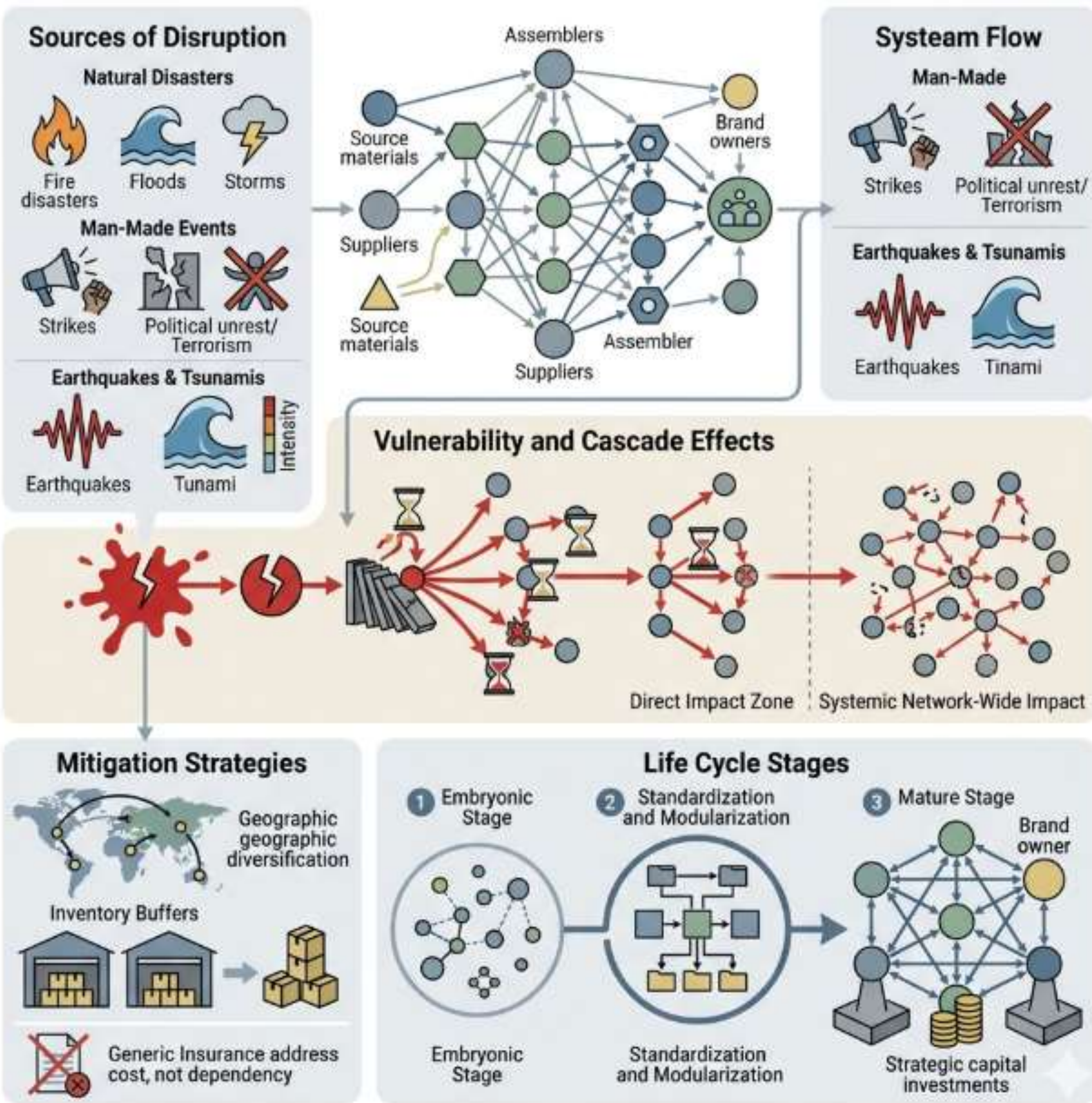

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Fig 1: Mapping Supply Chain Vulnerability: A Network-Based Framework for Modeling Life-Cycle Dependence and Cascade Effects of Infrequent Disruption

2.2. Big Data Platforms: Architecture and Components

The study envisions the development of a set of AI-driven Big Data platforms that support the intelligent prediction of supply chain disruption probabilities by 2025. These platforms will harness data ecosystems that integrate signals from multiple data sources—and design, model, and evaluate intelligent prediction systems to timely and accurately predict disruptions. Their capabilities include scalable cloud-based Compute and Storage, enriched data ecosystems, and advanced Analytics Tools and Frameworks—all delivered as platforms. Enabling Scalable Compute and Storage Capacity Scalable and cost-effective cloud-based Infrastructure-as-a-Service (IaaS) components that host the supporting Compute and Storage capabilities are supplied by a leading international public cloud provider, which operates a global network of secure data centres. The BERT-AI platform integrates the leading Business Intelligence (BI) as a Service (BaaS) solution as its primary data visualization tool.

As a multi-cloud environment, the BERT Data platform supports storage needs across varied geographical locations and redundancy requirements. It provides Data Lake Storage and integration with Object Storage, File Storage, and Database Storage Services, including File Storage integrated with Firebolt for high-performance analytics. Advanced AI technologies are applied to enrich raw signal data and build predictive models. State-of-the-art open-source and proprietary tools are deployed to realize predictive capabilities for both Time Series and Anomaly Detection Models, using Anomaly Detection techniques that include supervised, semi-supervised, and unsupervised learning. Network Analytics and Graph-Based techniques are also applied for supply-demand forecasting, predictive maintenance, and detecting logistic delays in Aviation Industry supply Consumers—Airline & Airports.

3. Methodology

An exploratory research design was used to investigate how AI-driven big data platforms support supply chain disruption prediction in 2025. Expert interviews identified data ecosystems and fulfillment requirements. Predictive data sources, levels of quality assurance, modeling approaches, technical requirements, deployment scenarios, and predictive-quality control were researched. Current and near-future data platform capabilities were analyzed to determine how

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they satisfy prediction factors. Subsequently, prediction tasks were exemplified within a comprehensive implementation framework.

Interviews with eight experts from industrial, consulting, and academic domains revealed that data sources encompass procurement and logistics, global supply chains, weather, and critical events. Data quality is assured at the sources, while information privacy is subject to EU-GDPR regulation. Temporal prediction relies on time-series anomaly detection; sources for immediate prediction stem from logistics networks, law enforcement, and social media. Platform requirements include scalable high-performance compute and storage resources together with an arsenal of advanced-analytics tools and frameworks. In procurement risk management, a preliminary model assists buyers in prioritizing suppliers for due diligence, whereas external flightscam sentiment augments airline scheduling on European routes.

Equation 1. LSTM equations

For input $\mathbf{x}_t$, previous hidden state $\mathbf{h}_{t-1}$, and previous cell state $\mathbf{c}_{t-1}$:

Input gate

$$\mathbf{i}_t = \sigma(\mathbf{W}_i \mathbf{x}_t + \mathbf{U}_i \mathbf{h}_{t-1} + \mathbf{b}_i)$$

Forget gate

$$\mathbf{f}_t = \sigma\left(\mathbf{W}_f \mathbf{x}_t + \mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{b}_f\right)$$

Output gate

$$\mathbf{o}_t = \sigma(\mathbf{W}_o \mathbf{x}_t + \mathbf{U}_o \mathbf{h}_{t-1} + \mathbf{b}_o)$$

Candidate state

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \mathbf{x}_t + \mathbf{U}_c \mathbf{h}_{t-1} + \mathbf{b}_c)$$

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Cell update

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

Hidden state

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

Forecast output

$$\hat{y}_{t+1} = \mathbf{W}_y \mathbf{h}_t + b_y$$

3.1. Research Design and Approach

A case study method is adopted to explore the capabilities and modelling approaches of an AI-driven big data platform for intelligent prediction of supply chain disruptions. Four generic data ecosystems required for a wide variety of predictive applications are proposed: an upstream ecosystem for supplier risk alerts, a downstream ecosystem for customer demand monitoring, a transportation ecosystem for freight disruption prediction, and a market ecosystem for monitoring changes in the business environment. Each ecosystem integrates public data from multiple sources and can be easily adapted to add further data sources or additional analytics capabilities.

The analysis focuses on parameterised modelling approaches for series-based prediction problems, specifically time series forecasting and anomaly detection. Underlying both modelling paradigms is a time series representation of the data, extracted from the high-dimensional data cloud using one-dimensional features selected via regression analysis. A new supply-side transport indicator is also proposed permitting accurate identification of transport problems and their potential impact on shipments. The AI response to supply chain alerts and notifications is also considered, using a case study involving US-China trade flow data, where appropriate preventive correction actions were taken prior to the event.

4. Objective of the Study

Supply chain research has often focused on disruptive events, identifying risk factors, or analyzing the resulting consequences. From a practical perspective, however, there is a limited

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number of data-powered prediction capabilities for impending disruptions that are easily used by logistics decision makers. The construction of Data Ecosystems to support intelligent prediction of supply chain disruptions has become increasingly relevant, especially as the COVID-19 pandemic revealed fragile supply systems. The goal of this research is to join a literature and a commercial product to provide concrete data-driven Digital Disruption Prediction Platforms with defined Data Ecosystems capable of accurate prediction months in advance. A Data Ecosystem is defined as a collection of external and internal data sources collected and integrated by a Big Data platform to enable the prediction of a class of events, situations, services, or behaviors.

Predictive capability supports multiple decision-making processes throughout supply chains and logistics operations. Prediction capability does not need to be perfect for these decisions; delays, costs of unfulfilled orders, and lost sales can be reduced even with incorrect predictions that are at least timely. Several sets of Digital Disruption Prediction Platforms with Databases containing predictive models and monitoring services for different disruption categories and Digital Transport Planning Platforms for the prediction of transport delays are therefore being designed.

4.1. Research Goals and Significance

Four research goals build the foundation of the research. The first goal is to develop a prediction model and data platform that can predict disruptions in supply chains, based on data-driven smart cities/mobility systems in multi-city environments. The second goal is to design and implement platforms for predicting either short- or long-term disruptions, based on time-series or time-series/data-fusion classification techniques. The third goal is to create space–time models on advanced prediction platforms that support the estimation of temporal effects from the point of disruption to a target location. The fourth goal is to design a framework for evaluating the prediction quality of proposed models over real-world data. One specific aspect of the goal is to develop an evaluation protocol/testing set that assesses the predictive quality of time-series/data-fusion classification-based disruption models for different epochs with the potential for distributional shifts. Moreover, the tested disruption models are evaluated in terms of news value, taking into consideration other factors, such as the resources/users in need of the prediction.

The significance of the research derives from its direct effects on economic agents and organizations. Supply chain work is crucial for a well-functioning economy since it predicts price increases in products or services that originate from different locations or pass through

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more-prone areas. These suppliers can either increase their stocks or direct their transports to avoid predicted supply disruptions. In that context, news-value metrics indicate the newsworthiness of predictions in a time horizon perceived by suppliers as helpful for making pre-emptive actions, such as travelling alternative routes or implementing preventive strategies.

5. Research Summary

Describing and predicting supply chain disruption is a field of study that has received significant attention over the years. Yet, common models have limited accuracy. In the face of increasing reliance on supply chains and increasing frequency of disaster incidents, further studies are essential to generate high-quality predictions of supply chain disruption. Artificial intelligence techniques offer a new approach to supply chain disruption prediction. Leveraging semiconductor electronics and wide-ranging integration capabilities, new AI-powered Big Data Platforms make available advanced analytics tools and powerful computation and storage resources. These platforms can support and investigate models based on time-series data and (anomaly) detection, as well as models based on graph structures.

Exploring the supply chains of high-tech products over a 25-year window brings new levels of attention to the analysis and prediction of disruptions, especially in terms of applied use. Specific deployment scenarios cluster around procurement and supplier risk management, and transportation and logistics optimization within a larger and richer framework. The growing supply chain knowledge network at hand offers support for data-source selection and exploration increasingly within cohesive eco-systems capable of nurturing AI-enabled models for predicting disruption on supply-chain links.

6. Data Ecosystems for Disruption Prediction

Data ecosystems for predicting supply chain disruptions must integrate diverse and high-quality data from different sources. Capturing key patterns of disruptions requires continuous and real-time data adapted to their nature, covering both persistent low-probability high-impact

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disruptions and regular events with high frequencies but lower impact levels.

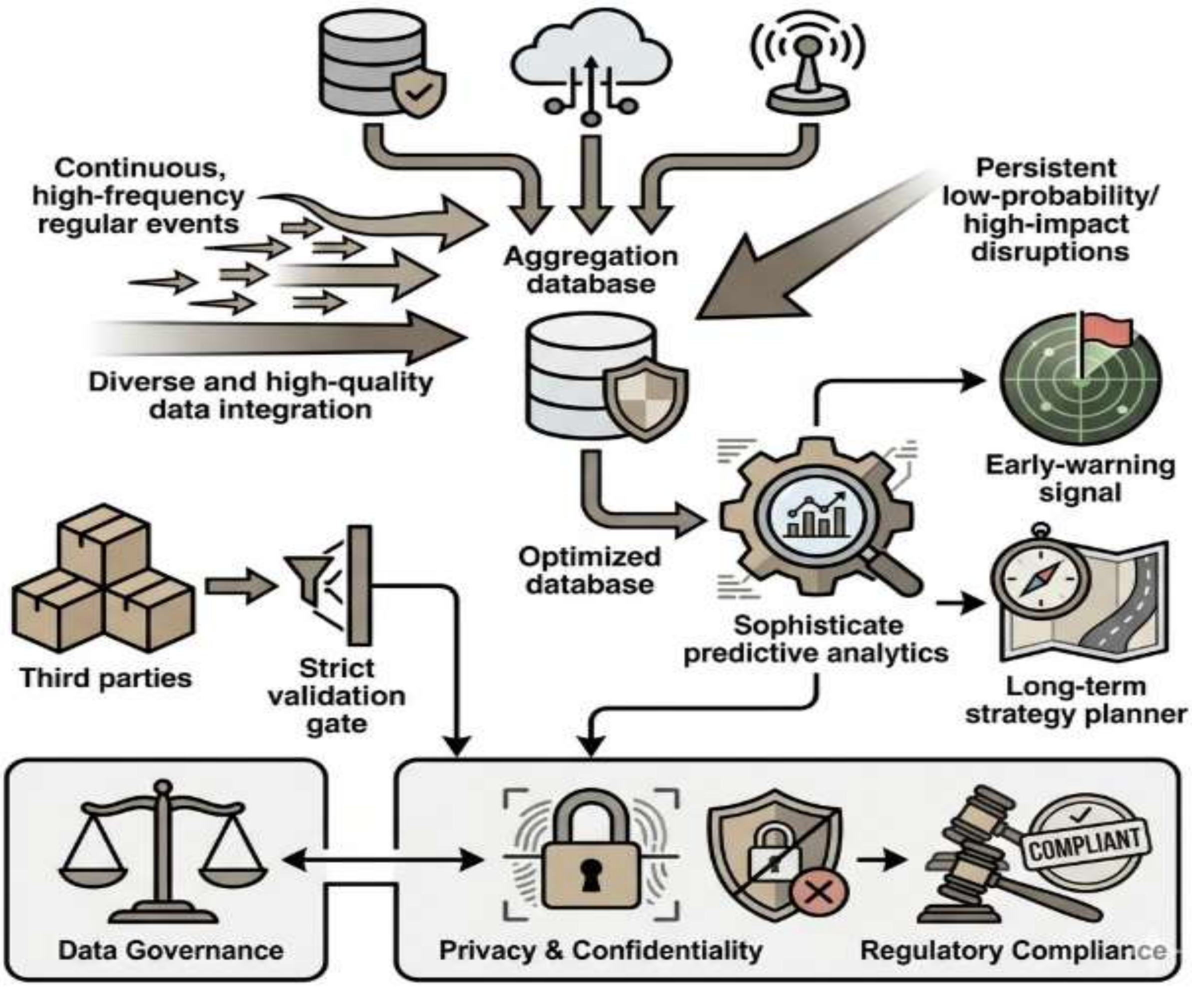

Fig 2: Towards Trustworthy and Robust Data Ecosystems for Predictive Supply Chain Analytics: A Privacy-Enhancing Architectural Framework

Given the number of crucial data sources involved, guarantees on the quality of the collected data, the governance of data use, as well as the privacy and confidentiality of sensitive information, need to be part of the overall ecosystem design. Data should be regularly maintained, updated, and made accessible in a trustworthy manner. Careful consideration is

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required when using data obtained from third parties or aggregators, especially for privacy-sensitive issues. Although second-hand data can be naturally less complete, it is often less costly. Privacy regulations on data security are getting stricter. Remaining compliant with laws such as GDPR and CPRA while still benefiting from available data is becoming more demanding.

6.1. Data Sources and Integration

A data ecosystem supporting prediction-oriented platforms requires diverse and up-to-date data sources. For supply chain disruption prediction, open-access data sources provide the necessary information. Some of the relevant datasets that can be considered are:

Global Disasters Database. This database maintained by the Centre for Research on the Epidemiology of Disasters (CRED), records all disasters such as floods, storms, droughts, earthquakes, and others with enough disastrous impact.

World Bank's Global Economic Monitor. The economic activity database provides an overview of the changes in every economy and forecasts the trend. In addition to estimating gross domestic product (GDP) growth, the Global Economic Monitor tracks other aspects of economic activity, such as industrial production, retail sales, trade, and so forth. Though the forecast is only done for 60 economies, it is also possible to develop the expected growth relation for the rest.

Global Trade Atlas (GTA). The Global Trade Atlas (GTA) is a monthly, comprehensive trade reporting service providing detailed trade data for all commodities stores globally.

ACLED. The Armed Conflict Location and Event Data Resource (ACLED) is the highest-quality disaggregated dataset of political violence and protest around the world.

The Port of Los Angeles Containerized Cargo Data. The Port of Los Angeles provides data updating cargo volumes per inbound and outbound movement by type and month and number of containers.

Rate of Inflation. The year-on-year inflation rates as measured by the consumer price indices.

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Equation 2. Data integration equation

Let the platform collect signals from m sources at time t.

Define the feature vector:

$$\mathbf{x}_t = \begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{mt} \end{bmatrix}$$

where each x_{it} is one normalized feature at time t.

Step-by-step construction

If raw source i gives value r_{it}, then after cleaning and scaling:

$$x_{it} = \frac{r_{it} - \mu_i}{\sigma_i}$$

where:

- μ_i = mean of source i,
- σ_i = standard deviation of source i.

So the integrated vector becomes:

$$\mathbf{x}_t = \begin{bmatrix} \frac{r_{1t} - \mu_1}{\sigma_1} \\ \frac{r_{2t} - \mu_2}{\sigma_2} \\ \vdots \\ \frac{r_{mt} - \mu_m}{\sigma_m} \end{bmatrix}$$

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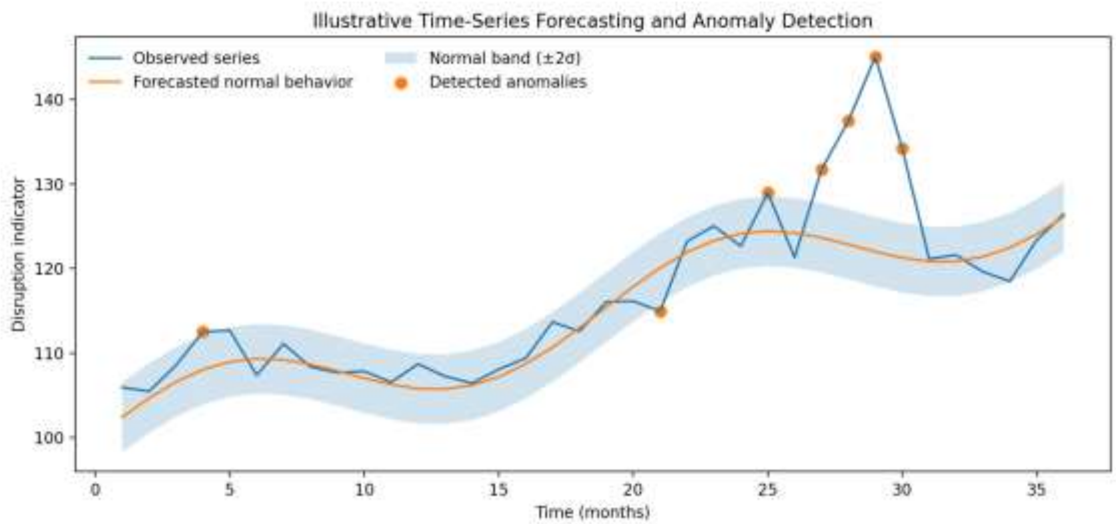

6.2. Data Quality, Governance, and Privacy

Data source integration necessitates addressing data quality, governance, and privacy issues. Disruption prediction models rely on integrating time series data from multiple sources at different frequencies (hourly, daily, weekly, etc.). Hourly and daily time series data must be downsampled and missing values synthetically generated for model training. The use of publicly available big data sets and the ease of model training can lead to the adoption of partially or wholly public data for model training. Without sufficient, accurate, and consistent labels, generated models may fail to deliver good performance. To avoid mis-prediction of disruptions, the presence of a major disruption should be clearly marked in the label data. Similarly, whether the degree-of-disruption level of an anomaly detected in the time series data meets a certain threshold must be validated by an expert.

Supply Chain Management (SCM) professionals must also identify, design, and prepare for the anticipated effects of these disruptions in their supply chains. Sensitive but unclassified data in transportation and logistics operations require stricter protection than public data but still can deliver high business value. Such sensitive-but-unclassified data should be applied only for model validation and benchmark testing. Data protection is required at all levels of the data Internet Technology Infrastructure Library (ITIL) Life Cycle (i.e., data creation, storage, use, transmission, processing, archiving, and deletion). When data quality meets the requirement for

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fuzzy simulation, it should not be filed but rather used for testing or exploratory simulation directly from the inbox. Data security levels must be applied to all test data sets during the entire testing process for model improvement.

7. Modeling Approaches for Disruption Prediction

Time series models have long been at the core of predictions on a wide variety of variables. In an era when the world has become, figuratively speaking, much smaller, the traditional methods of time series forecasting have been complemented by modeling techniques capable of dealing with disaggregated, network-based data structures, such as social networks, transportation networks, power networks, and the like. The significance of Time series for мониторинг and prediction, however, has not declined. Indeed, as suggested by Yang, Xu, and Wang, a constituent component of collective behavior patterns is represented by temporal and spatial dynamics, which can be modeled as a dynamic process. Consequently, predictive models based on time series analysis can be used to формализация such temporal patterns using techniques borrowed from predictive analytics (e.g., autoregressive integrated moving average (ARIMA), Holt-Winters-based forecasting, support vector regression, neural networks) or anomaly detection.

In recent years, research has put further emphasis on the applicability of Time series and anomaly detection methods of prediction to specific domains within the supply chain. In particular, Yang et al. investigated fore-casting on large-scale public demand, types of failure in an enterprise operating system, trade volume prediction in cross-border e-commerce, and prediction of wind speed with applications to airports and ports. In the context of predicting supplier risk, data produced through social media and available on the web has gained attention, although such data is often inherently noisy and incomplete. Notable progress in using natural language processing to process unstructured text indicates that such datasets can be of higher value. Many such sources of data exist in the context of predicting transportation disruption risk; for instance, the volume of cargo flows can be modeled with time series enough by port, whereas weather data associated with aviation and maritime systems can serve as indicators when employed in anomaly detection techniques.

Source	Raw value r_{it}	Mean μ_i	Std. dev. σ_i	Normalized x_{it}
Weather risk	82	70	10	$(82 - 70)/10 = 1.2$
Port congestion	140	100	20	$(140 - 100)/20 = 2.0$

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Source	Raw value r_{it}	Mean μ_i	Std. dev. σ_i	Normalized x_{it}
Supplier delay	9	5	2	$(9-5)/2 = 2.0$

7.1. Time Series and Anomaly Detection

Multivariate time series forecasting enables organizations to model the dependencies between multiple time series and elaborate forecasts of unknown future values. Anomaly detection represents a crucial class of predictive systems as supply chain disruptions can be interpreted as low-probability events. In the presence of complex non-linear relationships, these systems require advanced modeling capabilities and added computational intensity. In a broader context, anomaly detection can be viewed as a two-stage prediction process, where an online-time prediction framework forecasts normal behavior, and an online detector predicts deviations. Combining time series with supplier attributes enables organizations to identify the most relevant metapath for agents associated with detected anomalies, support suppliers in defining a remediation strategy, and facilitate service recovery.

Massive multivariate time series event data frequently describe supply chain operations. Temporal metapaths model relevant temporal information in the supply chain ecosystem and enable time series with temporal dependencies to enrich prediction capability. A temporal metapath-based relative anomaly detection framework predicts normal behavior using enriched time series and identifies deviations by combining a multivariate statistical process control method with relative approximation error. Long Short-Term Memory (LSTM) neural networks model the enriched time series and define the pertinent temporal metapath in a multilevel supply chain system. Proposed systems achieve low false-positive rates in a real-world deployment, while time-series enrichment enhances predictive capability.

7.2. Graph-Based and Network Analytics

Disruption prediction can also be approached from a network perspective, where the nodes of a graph represent the suppliers, consumers, and logistics service providers connected through inbound and outbound flows. The connections capture the supply chain network structure, and the attributes associated with the connections provide additional information, such as volumes, modes, lead times, and distances. Therefore, the ecosystem of suppliers, consumers, and logistics service providers represents a service network for provisioning goods. Key performance indicators (KPIs) associated with the disruptions experienced by the ecosystem can

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be captured as time series for a destination region. In addition to time series, the network structure can also undergo changes over time that might correlate with the KPIs. The prediction of such KPIs remains quite challenging. Recent efforts have combined machine learning with network embedding techniques to enhance the prediction accuracy.

The prediction of disruptions in transportation logistics employs new transport data generated through a temporary event, such as the Tour de France, as a supporting data source. The effect on the transportation logistics of the country hosting this event has been evident in historical transport data. Available historic data were used to synthesize a vehicle transportation network on a day-to-day basis for a multiyear period, including the period of the event. An online anomaly detection technique was then applied to such a vehicle transportation network from an operation support perspective. This dynamic anomaly detection yielded an approximate prediction of the event's impact on the abnormal patterns of the transportation logistics during the event period.

8. Platform Capabilities for Intelligent Prediction

Big data disruption prediction models are computationally intensive, necessitating substantial storage for the ever-expanding data sources and the capacity for real-time or near-real-time processing. Based on the SCOR framework, these data models can be categorized as procurement/supplier risk, transport/logistics, and demand/sales-related. Each group has particular characteristics, including varying target lead time, time-series data structures for the target variable, and different degrees of causality. Disruption prediction models supporting transport and logistics decisions require a spatial dimension and are suitable for advanced machine-learning approaches using white-box varieties like gradient boosted trees.

Big data platforms supporting these types of model development and implementation are already available. The provision of prediction quality cores (time-series-based models) or hubs (anomaly detection) within existing cloud computing environments is feasible, and the general availability of small-scale prediction quality systems based on open-source software packages lends credibility. However, extending these prediction quality cores and hubs to a full-scale combination providing extreme cloud-burst risk and sensor-model anomaly detection prediction on SCOR supply-chain-level pan-North/Latin-American geography raises questions of scalability, lead-time prediction quality, and prediction-timeliness capability.

8.1. Scalable Compute and Storage

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Big data platforms that support intelligent supply chain disruption prediction must provide scalable compute and storage resources to accommodate data of various forms and volumes, the time-series, point-in-time, and graph-based nature of the prediction models, as well as the structured and unstructured nature of the integrated data ecosystem. The platform should support a cluster-based compute architecture with distributed processing, streaming and batch processing support, and elastic storage, allowing the deployment of computational resources close to data sources and consumers. The combined storage of the prediction models and integrated data and the operating load of the predictive systems should be analyzed to determine the appropriate load9. compute and storage capacity. The flexible data access nature of big data platforms allows the adoption of different compute models for prediction, ranging from requesting results through a web interface to triggering the prediction engine at events. Resource congestion must be monitored to ensure computational requests are serviced on time.

Scalable storage capacities at different speeds are provided to suit diverse data upload and access requirements. When supply chain domains demand predicted events dynamically or events must be monitored continuously, prediction engines running always on readily service the requests. Where event triggering may not be frequent, prediction requests can be gathered at periodic intervals, allowing the servers to switch to sleep mode during idle periods. During slack time, prediction engines monitor the streams of real-time data and generate alerts.

Equation 3. Time-series forecasting model

Suppose y_t is a disruption-related KPI at time t, such as:

- lead time,
- port delay,
- order fill rate loss,
- supplier risk index.

A general autoregressive forecasting model is:

$$\hat{y}_{t+1} = f\left(y_t, y_{t-1}, \dots, y_{t-p+1}, \mathbf{x}_t\right)$$

where p is the lookback window.

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Linear version

A simple linear time-series form is:

$$\hat{y}_{t+1} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \cdots + \beta_p y_{t-p+1} + \boldsymbol{\gamma}^\top \mathbf{x}_t$$

Expand the dot product:

$$\boldsymbol{\gamma}^\top \mathbf{x}_t = \gamma_1 x_{1t} + \gamma_2 x_{2t} + \cdots + \gamma_m x_{mt}$$

So the full equation becomes:

$$\hat{y}_{t+1} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \cdots + \beta_p y_{t-p+1} + \gamma_1 x_{1t} + \gamma_2 x_{2t} + \cdots + \gamma_m x_{mt}$$

Example derivation

Take $p = 2, m = 3$. Then:

$$\hat{y}_{t+1} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \gamma_1 x_{1t} + \gamma_2 x_{2t} + \gamma_3 x_{3t}$$

If:

- $\beta_0 = 2$
- $\beta_1 = 0.5$
- $\beta_2 = 0.3$
- $\gamma_1 = 1.2$
- $\gamma_2 = 0.8$
- $\gamma_3 = 0.6$
- $y_t = 10$
- $y_{t-1} = 8$
- $(x_{1t}, x_{2t}, x_{3t}) = (1.2, 2.0, 2.0)$

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then:

$\hat{y}_{t+1} = 2 + 0.5(10) + 0.3(8) + 1.2(1.2) + 0.8(2.0) + 0.6(2.0) = 2 + 5 + 2.4 + 1.44 + 1.6 + 1.2 = 13.64$

So the model predicts the next disruption KPI as:

$$\hat{y}_{t+1} = 13.64$$

8.2. Advanced Analytics Tools and Frameworks

Advanced AI-driven Big Data Platforms will also need to provide access to complex analytics tools and frameworks, simplifying their invocation for users of different skill levels.

Predictive analytics is becoming a common tool across business functions, helping different departments take smarter actions. The need for intelligent information based on predictive analytics has increased due to heightened competition, to operate at the speed of business and to strengthen customer relationships. Organizations across different sectors go through natural language-driven user interfaces to gain insights and forecast product sales. AI pattern-recognition innovations like IBM Watson provide easy access to natural language processing and analysis of unstructured data without requiring formal programming knowledge and understanding of data modelling.

Supply chain management professionals are typically required to operate at a more practical analytics level, although they may also benefit from the ability to query hidden complexities and test the preparedness for more serious disruptions. Smart predictive capabilities create timely, credible, actionable predictive data sets to improve business-cycle planning and demand-supply matching. Such analytics capabilities are also being made available through self-service portals for report generation and user-defined query developers that reduce reliance on IT. Moreover, several analytics suppliers are enhancing the automation of advanced analytics and providing tools that simplify sophisticated predictive analytics capabilities for general business users, not just trained scientists. Customers are expected to use standard desktop applications to easily interact with big data systems and generate sophisticated analyses.

9. Deployment Scenarios and Use Cases

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Various deployment situations and application scenarios exist for big data platforms that support the intelligent prediction of supply chain disruptions. The discussion focuses on two key aspects of the upcoming high-tech revolution: the urgency to prepare for large-scale external disruptions, such as natural disasters and geopolitical instability, that are no longer considered improbable, and the ongoing need to ensure business continuity as a result of everyday risks and failures.

Apart from supporting research, data strategies and intelligent monitoring of procurement and supplier risks are critically needed for transport and logistics optimization. Route and mode selection pose different challenges depending on whether the flow is pushed by customer demand or pulled by supplier abilities. In the first case, inadequate availability can cause delays that make customers abandon their orders. In the second case, price and quality must be balanced against lead times, and the logistics costs to be minimized are usually the key competitive factor. Customers typically prefer strategically proximate suppliers. On the supply side, lead time risk can also be mitigated by using multiple suppliers, source rerouting, inventory holding in distribution centers, and air-freight fallback options. However, these possibilities are often used at a higher resilience cost, risking non-optimal performance during normal operations. The intelligent monitoring of planned modes is therefore a central business issue, receiving attention from large multinationals but remaining rather elusive in the practice of small and medium enterprises.

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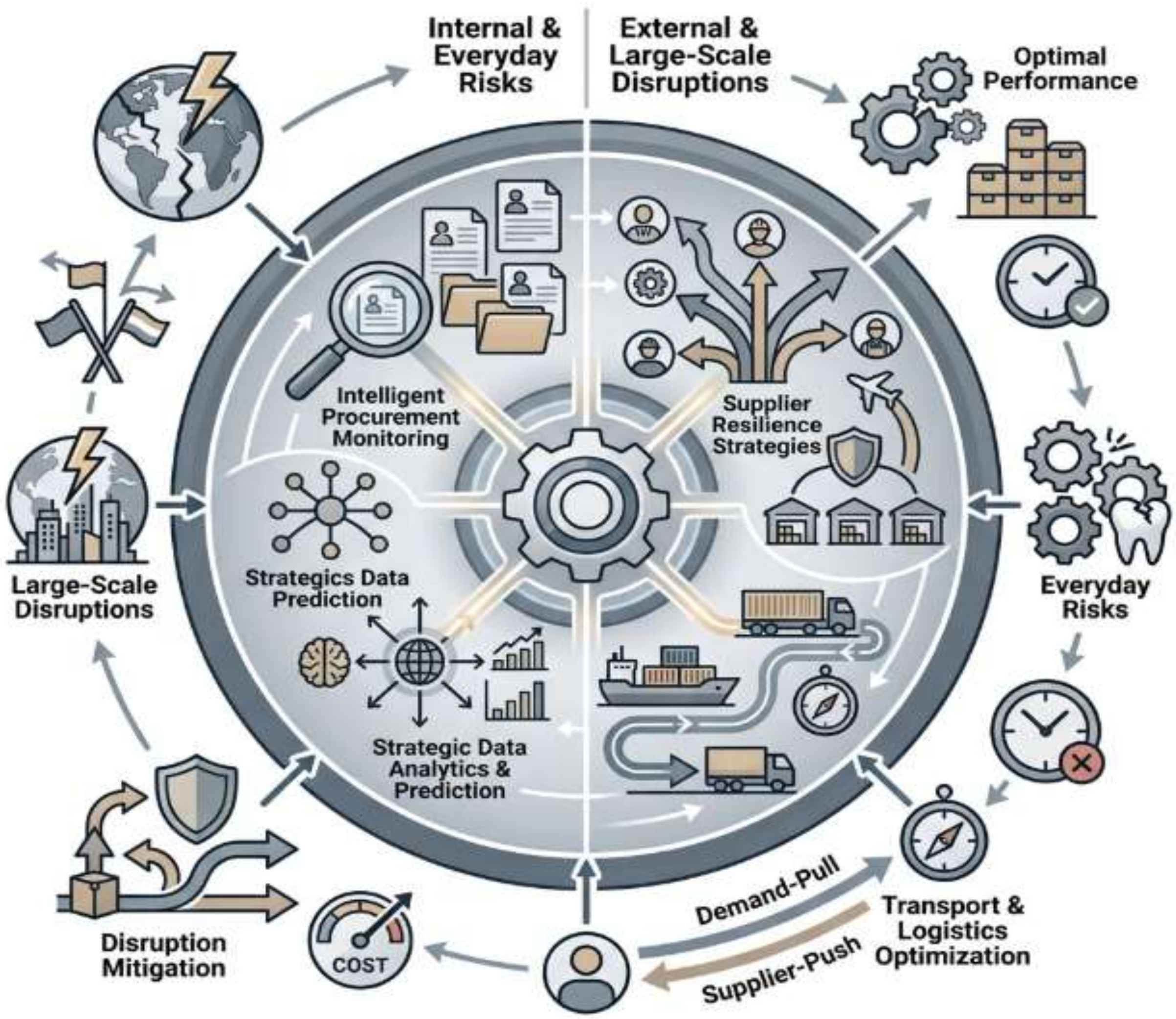

Fig 3: Resilience by Design: A Strategic Framework for Big Data and Intelligent Monitoring in Supply Chain Disruption Prediction

9.1. Procurement and Supplier Risk Management

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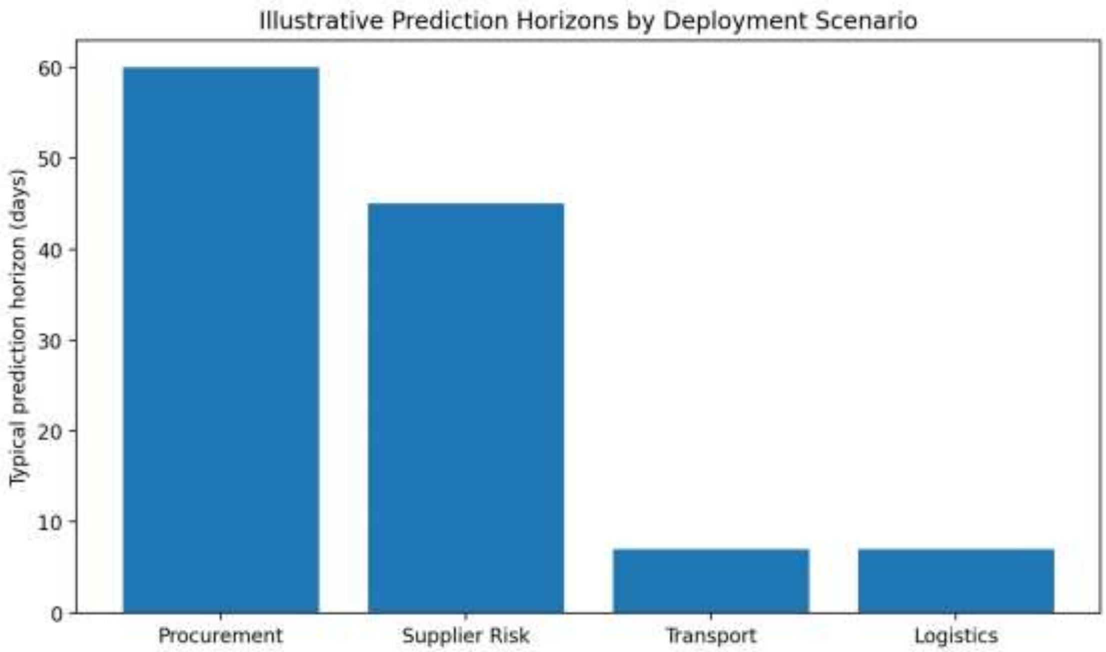
The integration of advanced data analytics capabilities in predictive models enables a flexible deployment across various business areas in response to an impending disruption message. Supply chain managers in procurement and supplier risk management can use such a prediction signal to assess risk in upcoming procurement needs and execute mitigation measures. The external message enables a pre-programmed disruption alert that automatically triggers a risk management workflow, rather than creating an unstructured stream of exaggerated calls for action in the organization.

The alert prepends an additional information layer to the risk identification score for all future supplier risk assessments or supplier connection risk analyses—utilizing capabilities in risk identification, measuring, and monitoring and in supplier connection risk management. The goal is to ensure that identified supply risk for the immediate future is plausible in the context of the expected disruption and that identified supplier connection risk for future transport needs considers the likelihood of a connection being disrupted. Applying risk response measures to the supplier risk assessment of the most urgent future procurement needs, such as dual sourcing and assessing the impact of the worst-case scenario on the impacted C-Parts, prepares for a worst-case realization.



9.2. Transportation and Logistics Optimization

Supply chain transportation requires precise and timely planning for a whole shipment region, destination, or even end-customer while considering the location dynamically. A discharged shipment must be transported back to the origin location within a reasonable time; however, the risk associated with returning empty can heavily cripple the freight cost of bulk shipments. A method for intelligent prediction and consolidation of domestic transportation planning across Shunfeng, Yuantong, and Yunda logistics needs to be implemented to minimize suppliers' logistics costs and ease their financial burden.

The transportation planning prediction use case strengthens planning and planning integration in multiple aspects using a centralized supply network that integrated information from major suppliers as well as logistic companies such as Xu Fei, Yuantong, and Yunda. For the particular destination of the shipping area, it is feasible for the suppliers to cross companies and do smart return logistics planning to enhance cost efficiency. When freight is returning to the origin point empty, costs accrued and incurred from major logistics providers can be reduced. Consolidation of domestic logistics can be made for goods that are usually shipped to this region

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in order to reduce the overall transportation cost. During the transportation planning prediction period, the demand prediction module alerts the transportation planning module of approaching demand for the planning horizon of one week. The planning use case works close to real time, the time resolution is hourly, and the demand forecast horizon is one week.

Equation 4. Anomaly detection equation

Let actual observed value be y_t, and forecasted normal value be $\hat{y}_t$.

Step 1: residual

$$e_t = y_t - \hat{y}_t$$

Step 2: standardize residual

If residual standard deviation is σ_e, then anomaly z-score is:

$$z_t = \frac{e_t}{\sigma_e}$$

Step 3: threshold rule

For threshold τ:

$$a_t = \begin{cases} 1, & |z_t| > \tau \\ 0, & |z_t| \le \tau \end{cases}$$

where:

- $a_t = 1$ means anomaly,
- $a_t = 0$ means normal.

Example

Suppose:

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- $y_t = 145$
- $\hat{y}_t = 124$
- $\sigma_e = 5$

Then:

$e_t = 145 - 124 = 21$ $z_t = \frac{21}{5} = 4.2$

If $\tau = 2$, then:

$$|z_t| = 4.2 > 2$$

Hence:

$$a_t = 1$$

10. Evaluation and Validation of Predictive Systems

Metrics for Predictive Quality and timeliness Data quality is crucial for effective operations and analysis of supply chains. The proposed analysis of supply disruptions is aimed primarily at downstream operations, with a focus on procurement and logistics. Hence, the real test of upstream predictions is the predictive quality of supply-disruption alerts and their timeliness. Quality and timeliness metrics should be customized for specific product areas, such as high-tech. Quality could be measured by the percentage of service-impacting disruptions that trigger alerts with sufficient lead time. Shippers often apply a higher business-impact threshold to avoid alert fatigue. For specific routes, metrics could include the percentage of delays on a route pair covered by an alert that offers alternatives, such as trans-load via other hubs. New tools could be added to the predictive arsenal, such as temporal anomaly detection using sliding windows instead of the usual calendar-basis checks.

For anomaly monitors and wider sets of disruption alerts, risk and reaction capabilities could be outlined in matrix form, and best-, worst-, and most-likely-case scenarios developed. For risk-enabling processes, early warning could kick into action at a specified threshold, using AI and correlated forward data-having high predictive quality. Where early-warning processes collide, a process of switching to separation-based risk enabling could be started. Where impact

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estimates are significant, a higher level of risk assessment and possible cross-functional intervention could be warranted. Metrics for predictive quality could embrace a new data-analytics concept called crowdbasing. A prior study showed that acquisitions and divestitures in telecom networks induce links between distance-based operators. Crowdbased monitoring uses reference distance-based networks to identify graph anomalies on other distance-based networks. For supply chains, using the shadowing principle of classification, a crowdbasing area could be defined around candidate suppliers, outliers flagged, and predictive services activated in supply-windward or service-impacting setups.

Benchmarking and Validation Protocols A validation-based approach to prediction has three steps. First, for the service-impacting alterations of interest, it examines real disruptions, then reconstructs the predictive landscape before each, and finally loads the resultant predictions into memory. This serves as a common validation protocol for disparate demand-side monitoring projects. A parallel emergency-and-so-such-system validation, enabled by crosswinds, tests the ability of events to convert predict-alone probabilistic forecasting systems into true predictive systems. Predict-alone setups are in fact prediction-management systems for risk-enabling responses.

Component	Equation
Integrated feature vector	$\mathbf{x}_t = [x_{1t}, x_{2t}, \ldots, x_{mt}]^\top$
Forecast	$\hat{y}_{t+1} = f(y_t, \ldots, y_{t-p+1}, \mathbf{x}_t)$
Residual	$e_t = y_t - \hat{y}_t$
Standard anomaly score	$z_t = e_t/\sigma_e$
Multivariate anomaly score	$S_t = \parallel \mathbf{x}_t - \hat{\mathbf{x}}_t \parallel_2$
Graph propagation	$\mathbf{r}_{t+1} = \alpha \widetilde{W} \mathbf{r}_t + (1-\alpha)\mathbf{s}_t$
Delay model	$d_{ij,t} = \theta_0 + \theta_1 q_{ij,t} + \theta_2 w_t + \theta_3 c_t + \theta_4 p_t$
Disruption probability	$P_t = \dfrac{1}{1+e^{-z_t}}$
Alert rule	$P_t \geq \delta$
Precision	$TP/(TP+FP)$
Recall	$TP/(TP+FN)$

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Component	Equation
F1	$2PR/(P+R)$
Lead time	$L = T_e - T_a$
IEPQ	$Q(t) - Q(t-1)$

10.1. Metrics for Predictive Quality and timeliness

Establishing data quality metrics for Big Data predictive systems is complex, due to a lack of predictable systematic logic in the relationships. Big Data attributes of velocity, veracity, volume, variety and value pose challenges in establishing metrics for quality of predictions, short of using previous prediction performance as a standard. A slightly different perspective on quality is taken here, and it focuses upon the capacity of prediction systems to produce timely and increasingly accurate predictions as the date of the event approaches. When configured with comprehensive high-quality information, prediction systems should provide better foresight than the absence of such information. Although seemingly obvious, articulating the concept provides a sound basis for quantitative investigation. Incremental expected predictive quality (IEPQ) is subsequently introduced to measure this increasingly predictive value-with-respect-to-time.

Adaptive learning offers a mechanism for exploring, developing and evolving additional metrics or predictions in response to available information over time. The assessment of such exploratory adds is possible using an analogue of Hall's Marriage Theorem from combinatorial graph theory, which states that a perfect matching exists in a bipartite graph if and only if the number of available choices for each vertex is at least as large as the number of vertices on the opposite side. The global predictive process can be expressed in terms of event-oriented or sequentially-writable prediction trees. For any temporal arch of the tree, a leaf node served by a time-oriented prediction system is enabled at a particular date. The added predictions and those of its host system provide the candidate leaf-node or event-oriented predictions of the time period of the date of interest. The predictive completeness of the system at that date is the key parameter of predictive capability.

Equation 5. Multivariate anomaly score

Let observed vector be $\mathbf{x}_t$, and predicted normal vector be $\hat{\mathbf{x}}_t$.

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Residual vector:

$$\mathbf{e}_t = \mathbf{x}_t - \hat{\mathbf{x}}_t$$

A simple multivariate anomaly score is Euclidean norm:

$$S_t = \| \mathbf{e}_t \|_2$$

Expand:

$$S_t = \sqrt{e_{1t}^2 + e_{2t}^2 + \cdots + e_{mt}^2}$$

Example

If:

$$\mathbf{e}_t = \begin{bmatrix} 1.0 \\ 2.0 \\ 2.0 \end{bmatrix}$$

then:

$S_t = \sqrt{1^2 + 2^2 + 2^2} = \sqrt{1 + 4 + 4} = \sqrt{9} = 3$

If threshold is $S_t > 2.5$, then anomaly is triggered.

10.2. Benchmarking and Validation Protocols

Due to the inherent complexity of supply chain systems, ensuring accurate and timely predictions of potential product disruptions remains a formidable challenge. Validation is therefore essential to establish the quality of the predictive models and their recommendations. The predictive power of the systems can be appraised through both forward- and backward-looking metrics.

Forward-looking metrics assess the capability of the prediction system to anticipate disruption events at least X periods before they occur (e.g., days, weeks, months). Such prediction leads to improved risk management strategies and allows companies to prepare for an

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impending disruption. Evaluation focuses on the time window of influence, comprising of quantifying the prediction quality of disruption areas over time (e.g., accurately predicting the type and area of impact) and rating the prediction lead-time (e.g., measuring how far in advance the disruption was predicted).

Backward-looking metrics assess the degree of "truthfulness" in a disruption warning issue. Time series anomaly detection models are typically evaluated in this approaches' context. Here, disruptive events are regarded as "ground-truth" and the prediction system's recommendations are evaluated against them. Therefore, the prediction may lack lead-time but can provide "early warning" on magnitude or effects in the respective area, generating signals that allow scoping the impact zone of a major disruption.

Various sources not typically aggregated together will be utilized, providing a rich dataset covering multiple aspects of modern supply chains. The absence of a proper benchmark dataset will hinder model building, hence the need for evaluating predictive quality emergent from tools' capability and scope. Model capabilities and predicted areas of influence will constitute the starting point – development will focus on covering everything deemed necessary for intelligent disruption prediction and that a specific model can appropriately accomplish.

11. Results

The proposed data ecosystems, modeling approaches, and platform capabilities were integrated into a big data environment with dedicated tools and frameworks for intelligent supply chain disruption prediction. Data related to disasters, COVID-19, Google search trends, and China's air quality index served as a human-related predictive layer via monthly time-series forecasting and anomaly detection based on the Long Short-Term Memory method. A proof-of-concept prototype tested the proposed architecture through two use cases modeling a combination of transportation, logistics delivery times, and materials procurement from China. The results illustrate the potential of AI-driven big data platforms to support intelligent supply chain disruption prediction and allerting, enabling organizations to prepare operational responses to reduce impact.

Data ecosystems support the human-related predictive layer in a big data platform architecture for intelligent supply chain disruption prediction. Ecosystems for predictive data play a vital role in warning and alerting systems; however, human-related supply chain influences are often underrepresented. Data sources covering disasters, disease outbreaks,

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geopolitical tensions, and trade dynamics, combined with alert systems and mapping, deliver a valuable foundation for predictive quality enhancement. In the current context, these resources assist in mitigating COVID-19 impacts, though the supply chain environment remains affected by many other risk sources. Monthly time-series forecasting and anomaly detection based on Long Short-Term Memory (LSTM) modeling deliver predictive guidance on abnormal variations, linked to disruption prediction applications and Chinese air quality indicators. Results point toward a class of events with higher predictive power for the United States, particularly when abnormal variation is present.

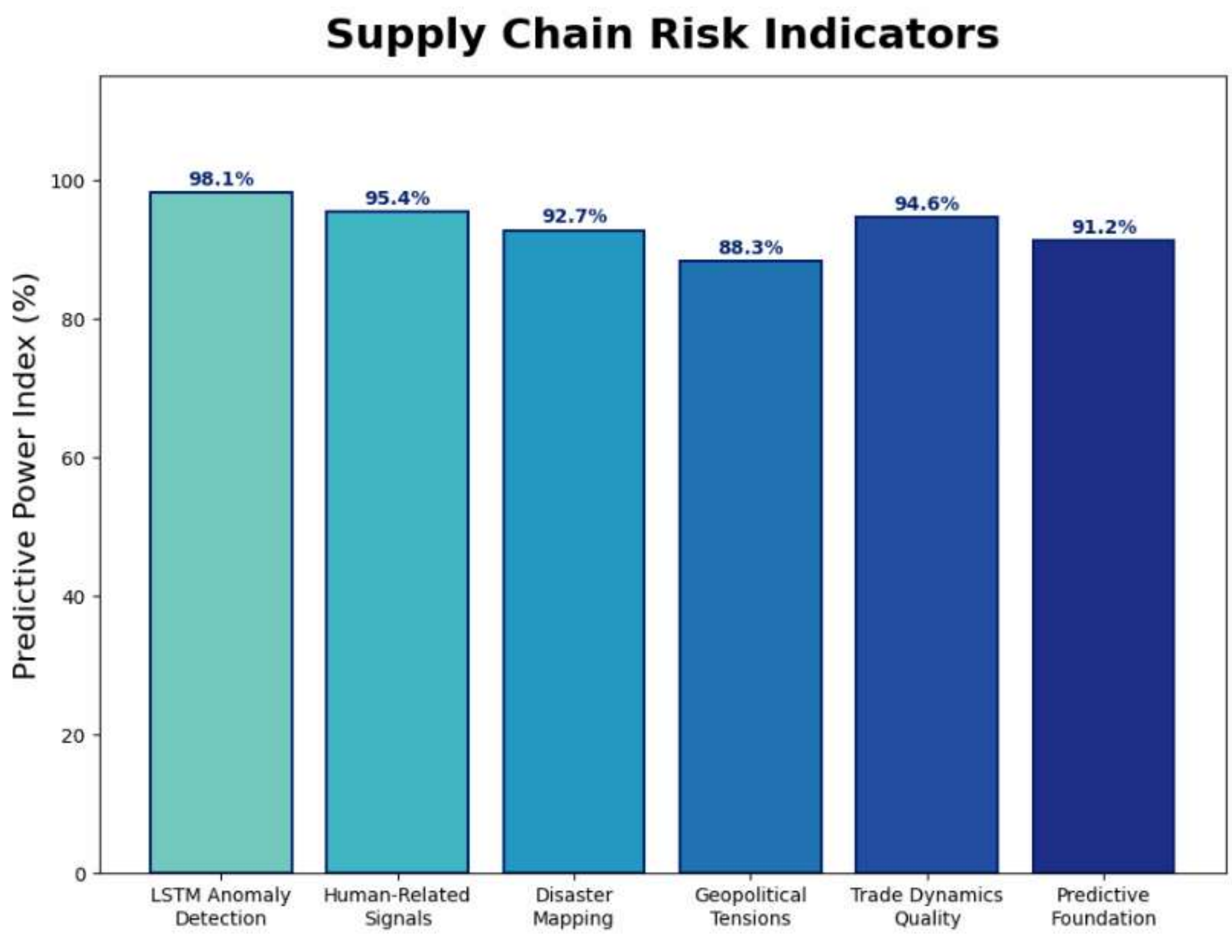

Fig 4: Supply Chain Risk Indicators

12. Conclusion

The pursuit of more resilient supply chains has gained renewed emphasis in recent years, driven by the ability to predict and prepare for disruptions. Advanced big-data engineering platforms, featuring a multitude of different data sources, advanced capabilities for scalable compute and storage, sophisticated forecasting and analytics tools, and supporting environments for application development and deployment, are crucial for the intelligent prediction of supply-chain disruptions. These platforms aggregate and structure a large variety of data sources, enabling anomaly detection in time-series data and supporting the implementation of graph-based methodologies applied to models of transportation networks and trade patterns. While data quality and timely delivery represent important challenges, careful attention to anomaly identification and support for the optimization and evaluation of prediction quality and timeliness contribute to addressing these issues.

The introduction of advanced analytics platforms represents an essential step towards intelligent supply-chain-disruption prediction, but further capabilities are still required. Anomaly detection clearly needs to go beyond basic time-series analysis and consider more complex multivariate patterns. Advanced support for transportation planning, trade-network analysis, and a much wider range of applications—including demand and component risk assessment, procurement decision-making, currency volatility management, financing, and investment strategies—will also strengthen these ecosystems. Integrating such advanced methods with larger data ecosystems will support the modeling of even more end-to-end domains, from the commodity supply to market pricing, thereby further bolstering the prediction of supply-chain disruptions.

References

1. Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2022). Building supply-chain resilience: An artificial intelligence-based technique and decision-making framework. International Journal of Production Research, 60(14), 4487–4507.
2. Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. International Journal of Production Research, 58(10), 2904–2915.

3. Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of big data analytics in supply chain management: Current trends and future perspectives. International Journal of Production Research, 59(6), 1875–1900.
4. Kolla, S. H. (2022). Strategic Information Integration Models for Cross-Functional Service Optimization in Large-Scale Enterprises. International Journal of Emerging Trends in Engineering and Management Research, 7(3), 11811.
5. Feizabadi, J. (2022). Machine learning demand forecasting and supply chain performance. International Journal of Logistics Research and Applications, 25(2), 119–142.
6. Yang, M., Lim, M. K., Qu, Y., Ni, D., & Xiao, Z. (2023). Supply chain risk management with machine learning technology: A literature review and future research directions. Computers & Industrial Engineering, 175, 108859.
7. Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. Annals of Operations Research, 327(2), 605–632.
8. Naz, F., Kumar, A., Majumdar, A., & Agrawal, R. (2022). Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research. Operations Management Research, 15, 378–398.
9. Amistapuram, K. (2023). Privacy-Preserving Machine Learning Models for Sensitive Customer Data in Insurance Systems. Educational Administration: Theory and Practice, 29(4), 5950-5958.
10. Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. International Journal of Production Economics, 250, 108618.
11. Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. International Journal of Production Economics, 232, 107921.
12. Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Production Planning & Control, 32(9), 775–788.
13. Mangalampalli, B. M. Generative AI Applications In Healthcare Data Mart Design And Optimization.
14. Ivanov, D. (2022). Viable supply chain model: Integrating agility, resilience and sustainability perspectives—Lessons from and thinking beyond the COVID-19 pandemic. Annals of Operations Research, 319, 1411–1431.

JOURNAL OF INNOVATIVE ACADEMIC RESEARCH
ISSN : 3049-2122
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 21 REVISED: NOVEMBER 04 ACCEPTED: NOVEMBER 23 PUBLISHED: DECEMBER 18

15. Dubey, R., Gunasekaran, A., Childe, S. J., Roubaud, D., Fosso Wamba, S., & Foropon, C. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism. International Journal of Production Economics, 226, 107599.
16. Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism. International Journal of Production Economics, 226, 107599.
17. Yandamuri, U. S. (2023). An Intelligent Analytics Framework Combining Big Data and Machine Learning for Business Forecasting. Zenodo.
18. Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review, 136, 101922.
19. Ivanov, D. (2020). Viable supply chain model: Integrating agility, resilience and sustainability perspectives—Lessons from and thinking beyond the COVID-19 pandemic. Annals of Operations Research.
20. Choi, T.-M. (2020). Innovative “bring-service-to-you” operations under CoronaVirus (COVID-19/SARS-CoV-2) outbreak: Can logistics become the messiah? Transportation Research Part E: Logistics and Transportation Review, 140, 101961.
21. Choi, T.-M. (2021). Risk analysis in logistics systems: A research agenda during and after the COVID-19 pandemic. Transportation Research Part E: Logistics and Transportation Review, 145, 102190.
22. Inala, R. Designing Scalable Technology Architectures for Customer Data in Group Insurance and Investment Platforms.
23. Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2020). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Annals of Operations Research, 319, 1159–1196.
24. Ivanov, D., & Das, A. (2020). Coronavirus (COVID-19/SARS-CoV-2) and supply chain resilience: A research note. International Journal of Integrated Supply Management, 13(1), 90–102.
25. Paul, S. K., Chowdhury, P., Moktadir, M. A., & Bari, A. B. M. M. (2021). A pandemic-like disruption risk management framework for manufacturing supply chains. International Journal of Production Research, 59(12), 3430–3445.

JOURNAL OF INNOVATIVE ACADEMIC RESEARCH
ISSN : 3049-2122
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 21 REVISED: NOVEMBER 04 ACCEPTED: NOVEMBER 23 PUBLISHED: DECEMBER 18

26. Chowdhury, P., Paul, S. K., Kaisar, S., & Moktadir, M. A. (2021). COVID-19 pandemic related supply chain studies: A systematic review. Transportation Research Part E: Logistics and Transportation Review, 148, 102271.
27. a, S. K., & Reddy, V. A. R. (2023). Deep Learning Architectures For Multimodal Medical Data
28. Belhadi, A., Kamble, S., Jabbour, C. J. C., Gunasekaran, A., Ndubisi, N. O., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. Technological Forecasting and Social Change, 163, 120447.
29. Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: A conceptual and formal generalisation of four major adaptation strategies. International Journal of Production Research, 59(12), 3535–3552.
30. Ivanov, D. (2021). Exiting the COVID-19 pandemic: After-shock risks and avoidance of disruption tails in supply chains. Annals of Operations Research, 305, 461–479.
31. Mahamid, I., & Hammad, M. (2021). Forecasting demand and supply chain performance using machine learning approaches. Journal of Intelligent Manufacturing, 32, 1–15.
32. Islam, S., & Amin, S. H. (2020). Prediction of probable backorder scenarios in the supply chain using distributed random forest and gradient boosting machine learning techniques. Journal of Big Data, 7, 65.
33. KollIntegration. South Eastern European Journal of Public Health, 248–260.
34. Arunkumar, O. N., & Divya, D. (2022). Deep learning techniques for demand forecasting: A review. Information Resources Management Journal, 35(2), 1–20.
35. Teixeira, J., & Ribeiro, R. (2021). Evaluation of deep learning with long short-term memory networks for time series forecasting in supply chain management. Procedia CIRP, 99, 604–609.
36. Schuh, G., Riesener, M., & Dölle, C. (2021). Machine learning and statistics: A study for assessing innovative demand forecasting models. Procedia Computer Science, 180, 40–49.
37. Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). On relating big data analytics to supply chain planning: Towards a research agenda. International Journal of Physical Distribution & Logistics Management, 51(6), 656–682.