

# Machine Learning Approaches for early Prediction of Supply-Chain Disruptions and Operational Risks

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## ABSTRACT

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The frequency and effect of supply-chain disruptions have increased in intensity and impact because of the growing global interconnectivity and complexity of their operation. Although the classic frameworks of supply chain risk management focus on the reactive resilience strategies, the innovations in machine learning provide the prospects of proactive early disruption identification. This paper introduces a systematic conceptual overview of machine learning solutions to early detection of supply-chain disruption and operational risks. The current approaches are divided into supervised learning models, time-series deep learning methods, graph-based network approaches, and anomaly detection systems. The review also examines the data usage trends and metrics of evaluation performance, and specifically those of early-warning performance and lead-time performance. The results have shown that despite the enhancements in the predictive accuracy, there has been little focus on multi-tier network modeling, integration of multimodal data and standardized early-warning evaluation models. This paper is based on the premises of the Dynamic Capabilities Theory, and the conceptual theory of predictive analytics as a strategic facilitator of proactive and adaptive supply chain risk management.

Keywords: Supply chain disruption prediction; Machine learning; Early warning systems; Operational risk; Supply chain resilience.

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## INTRODUCTION

Over the last twenty years, the world supply chains have grown more and more complex, interconnected and geographically dispersed. Globalization and other aspects of lean production like just-in-time manufacturing have made operations more efficient and cost-effective in terms of inventory but have also made the companies more vulnerable to disruptions (Christopher and Peck, 2004; Ivanov and Dolgui, 2020). The COVID-19 pandemic, geopolitical unrest or natural disasters, and congestions in the ports have proven that even localized disturbances may spread across several levels of supply networks and lead to serious operation and financial outcomes (Ivanov, 2020; Queiroz et al., 2020). The supply chain disruptions are low-frequency but high-impact events that may severely impact on the continuity of operations, the stability of revenues and reputation of the firms (Tang, 2006). The conventional supply chain risk management (SCRM) factors are based on reactive measures, such as buffer stocks, dual sourcing, and contracts (Ho et al., 2015). These techniques may increase resilience, but they do not in most cases provide real time or early predictive accuracy. The growing access to big-scale operational information, tracking logistics, and other sources of data has provided the space to transition towards reactive risk reduction to proactive and predictive disruption management. Machine learning (ML) has become less of a prospective research method to model nonlinear relationships between the data supplied to the supply chain in high dimensions (Baryannis et al.,

2019). In contrast to the classical statistical approach, ML models have the ability to handle heterogeneous data such as structured enterprise resource planning (ERP) data, shipment tracking logs, weather data, and even unstructured text such as news reports to determine trends that can reveal a disruption. Recent papers have examined the use of ML to predict demand, evaluate suppliers' risk and detect anomalies in operations (Carbonneau et al., 2008; Choi et al., 2018). Nevertheless, the research on early supply-chain disruption identification, especially on multi-levels in a network, is still scattered and unexplored.

COVID-19 crisis was a global crisis that accelerated the study of predictive supply chain analytics. The article by Ivanov (2020) has shown that the systemic effect of supply interruptions due to the pandemic can be demonstrated with the help of simulation-based models, which suggests that early-warning systems require data. In the same way, Queiroz et al. (2020) highlighted such enablers of supply chain resilience as digital transformation and analytics. Regardless of these developments, the majority of current methods are either based on the modeling through simulation or emphasize on the post-disruption analysis instead of early predictive detection of a disruption based on machine learning. There is also a critical research gap in creating and integrating machine learning solutions to be able to provide an early warning of operational risk and disruption of supply-chain. The predictive systems may allow the companies to take mitigation measures like switching suppliers, rerouting logistics, or changing production timings before the disruption becomes a reality. Besides, the integration of network-level dependencies and alternative sources of data is a developing yet unexploited niche. This paper will analyze machine learning techniques to predict pre-emptively supply-chain disruption and operational risk. The research aims to add to the growing intersection of the supply chain risks management, predictive analytics, and intelligent decision-support systems by synthesizing the available literature and outlining gaps in the literature critical methodologies.

### LITERATURE REVIEW

#### Development of Supply Chain Risk Modelling Approaches

The initial approaches to modeling early supply chain risk were mainly deterministic optimization and stochastic programming, along with disruption scenarios based on the use of simulation (Snyder et al., 2016). These models were useful in determining network resilience given probabilities of disruptions assumed, but they tended to have strong parametric assumptions and preset risk scenarios. With the emergence of increasingly complex and multi-tiered supply chains, scholars noticed that the simple models were no longer useful in modeling the dynamic risk propagation. Perspectives based on the network later came into view. Supply chains became more conceptualized as multifaceted adaptive networks in which disruptions are spread in a nonlinear fashion throughout interconnected nodes (Kim et al., 2015). Centrality, clustering and node criticality were found to be network topology characteristics that affected systemic vulnerability. Nevertheless, the classical network models were not very predictive and were more descriptive with no early disruption detecting potentialities.

#### Machine Learning Supply Chain Analytics

As the phenomenon of big data systems and electronic supply chains expanded, machine learning (ML) methods started having a transformative effect on supply chain analytics. Waller and Fawcett (2013) suggested that predictive analytics would take center stage in the competitive advantage in operations management. Later studies have shown that the ML algorithms outperform the classical statistical models in demand prediction, supplier assessment, and inventory optimization (Kamble et al., 2020). Recent systematic reviews point to the fact that the use of supervised learning techniques, including Random Forests, Support Vector machines, Gradient Boosting, and Deep Neural Networks, has become widely used in the field of operational risk assessment (Min, 2010; Wang et al., 2016). These models are capable of dealing with high-dimensional, nonlinear data and detecting subtle patterns that will cause operational failures. However, the majority of applications are limited to the demand or inventory forecasts, but not the disruption prediction.

Recurrent neural networks (RNNs) and long short-term memory (LSTM) are deep learning frameworks that have shown good performance in identifying temporal relationships in logistics and operation data (Fang et al., 2020). Nevertheless, there is little empirical research on their efficacy in forecasting infrequent disruption events as a result of imbalance in the classes and very sparse events labelling.

### **Early Detection Systems and Anomaly Detection**

A similar body of work is devoted to the detection of anomalies and early warning mechanisms in the field of operations. Autoencoders, isolation forests and change-point detection models have been implemented in an unsupervised and semi-supervised mode to detect anomalies in production systems and logistics flows (Chandola et al., 2009). Such methods are especially applicable in the cases when there is limited disruption data that is labelled. Finance and cybersecurity operational risk literature shows that the accuracy of early detection is high when anomaly detection models are combined with supervised classifier in hybrid systems (Bolton and Hand, 2002). Nevertheless, these early-warning systems that are hybrids are under-investigated when applied to supply chains. The issue is that it is difficult to tell the difference between normal variability of operations and significant antecedents of disruption.

### **Multi-Tier Supply Networks and Graph Based Learning**

Conventional supply chain risk management typically concentrates on first-tier supplier as opposed to the upstream dependencies. The recent disruptive incidents of high complexity have demonstrated that multi-tier visibility is essential (Luo et al., 2020). To overcome this shortcoming, scholars have started modeling supply chains as graph structured data.

Graph based methods of learning such as Graph Convolutional Networks (GCNs) and attention-based graph models can be used to apply node attributes and network topology (Wu et al., 2020). Graph neural networks (GNNs) have been shown to be superior at predictive capability in interdependent risk modeling in parallel tasks, including fraud detection and financial contagion (Zhou et al., 2020). However, their use in modeling disruption propagation in supply chains is still in its infancy, and does not have standardized benchmarking data. It can be argued that network-aware ML methods can better represent ripple effects compared to independent time-series models based on the literature. Nonetheless, empirical confirmation in the real-world environment of supply chain is scarce.

### **Assimilation of the Alternative and Unstructured Data**

The other direction of emerging trends is to use other sources of data, such as news sentiment, satellite imagery, shipping data, and weather information, to predict operational risk. Risk indicators have been gathered using text mining and natural language processing (NLP) to make the most out of news articles and social media feeds (Loughran and McDonald, 2016). Models of event detection have demonstrated to be effective in detecting early signs of any disruption in geopolitical or environmental factors. Disaster forecasting and financial risk modeling studies show that the combination of structured data on operation and unstructured text enhances the predictive performance (Huang et al., 2018). In spite of this data, multimodal integration of data in supply chain disruption prediction models is not very common, mainly because of the limitation of accessing data and the complexity of computing. When combined, the discussed literature indicates the apparent development of the methodology of disruption modeling into the form of data-driven and machine-based predictive modeling and, more recently, network-sensitive and multimodal predictive modeling. Nevertheless, the extent of interrelation among these streams of methods is minimal. This evolutionary path is summed up by Figure X.

As Figure 1 depicts, the study of disruption prediction has been changing gradually in the past twenty years. Initial research was based mainly on classic operations research and simulation-based resilience modeling. As enterprise data systems grew, monitored machine learning methods became popular, then big data analytics and deep learning architectures were included. Graph-based learning techniques have more recently been investigated with a view of capturing network interdependencies within multi-tier supply chains. Yet, most multimodal early-warning systems are not fully developed yet and represent a nascent research area. This evolutionary trend promotes the imperative to implement well-organized structures that run hand in hand with methodological sophistication coupled with acting in the form of identified risks.

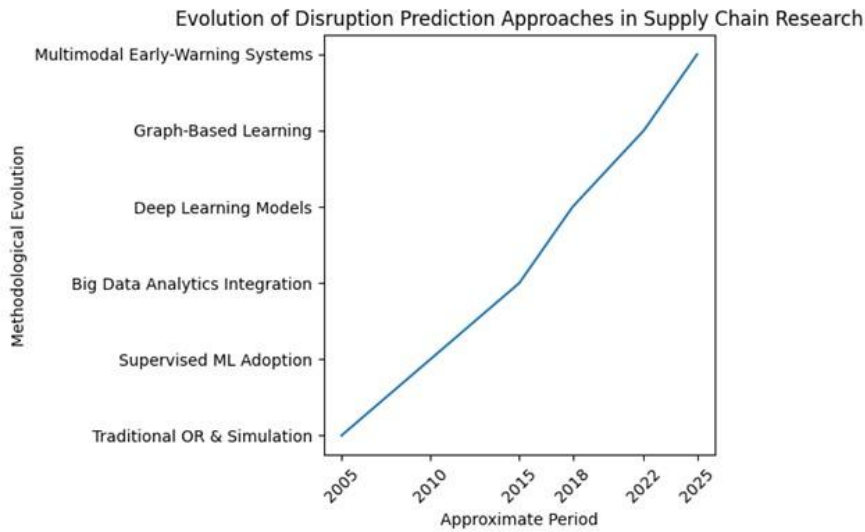


Figure 1. Evolution of Disruption Prediction Approaches in Supply Chain Research

### Research Gap

Despite the popular applications of machine learning in demand forecasting, inventory optimization, and various other fields, the systematic application to predict disruption and operational risk in a supply chain at an early stage is not actively used. The literature so far dwells mainly on the reactive resilience mechanisms, simulation-based impact analysis, or firm level risk assessment as opposed to the proactive and data based early-warning systems. Besides, scant focus has been on integrating multi-tier network structures and other external data sources into coherent predictive models. Lack of standardization of measures of evaluation and benchmark data also limits the feasibility of application and the comparative verification. As a result, it is evident that there is a necessity of systematic studies that combine network-conscious and multimodal machine learning methods to disrupt timely. The fact that machine learning methods and supply chain risk studies are limited in intersecting with early-warning system development (Figure 2) indicates the research area at their intersection that is underdeveloped.

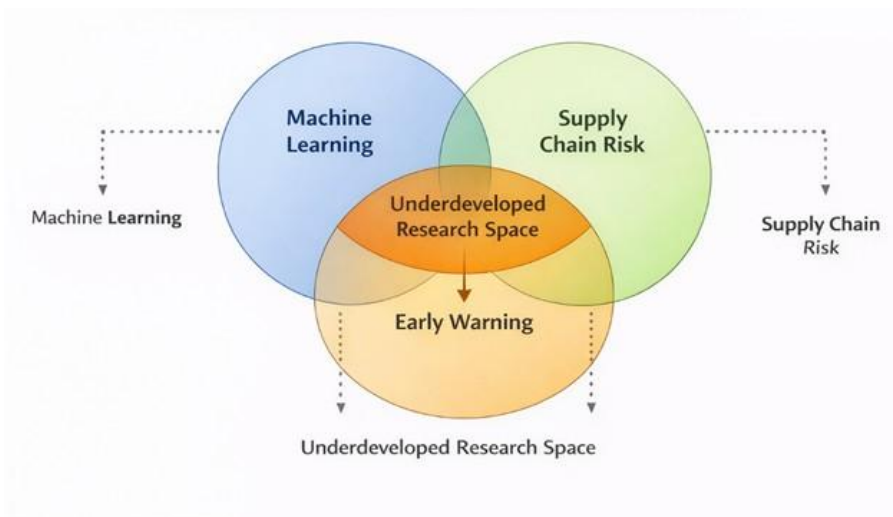


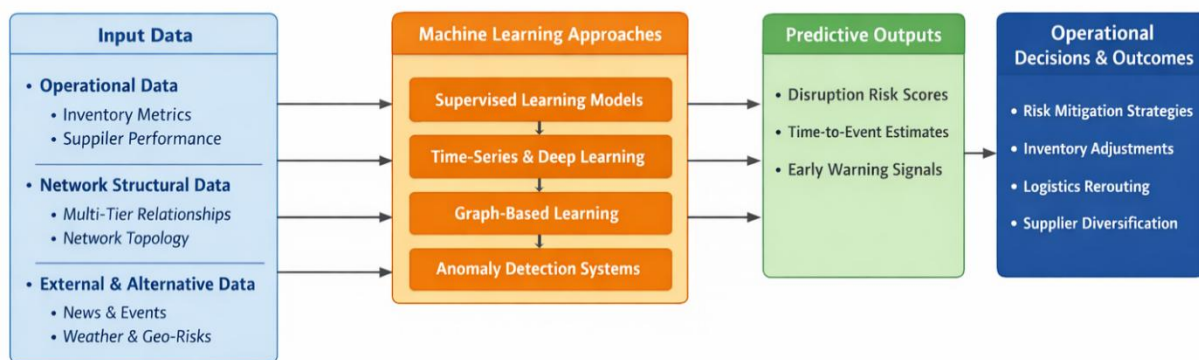
Figure 2. Research Gap in Early Supply-Chain Disruption Prediction

### METHODOLOGY

This paper takes a conceptual review approach where the systematic study of machine learning methodologies is done to identify methods of supply-chain disruptions and operational risk prediction at the earliest stage. It is not aimed at creating or empirically testing a certain predictive model, but at synthesizing the existing approach to

analysis, comparing methodological orientations and finding new research directions in the direction. A literature search was done systematically in the large academic databases, such as Scopus, Web of science, IEEE Xplore, and ScienceDirect. Search strategy was based on the positioning of the keywords of supply chain disruption, operational risk, early warning systems, predictive analytics, and machine learning. Peer-reviewed journal articles and conference proceedings published in credible sources only were taken into consideration to achieve academic rigor. The studies were sorted by the inclusion criterion of applying explicitly machine learning, deep learning, graph-based modeling, or anomaly detection to the issues related to disruption prediction, operational risk assessment, or resilience analytics. Articles that solely dealt with demand forecasting or general supply chain optimization and did not include a risk or disruption factor were filtered out. After the identification, the identified studies were evaluated with the help of a systematic classification scheme. The review systematizes the literature on three fundamental analysis dimensions, that is, the kind of the machine learning-based methodology used, nature of the sources of data used and evaluation approaches taken. Methodologically, there are supervised learning models, time-series deep learning models, graph-based network learning models and frameworks of anomaly detection. Data wise, attention is given to the presence of structured operational data, multi-tier supply network data, or other and unstructured data sources including textual event data and environmental data. Regarding evaluation, specific focus is put on predictive performance indicators and to what extent studies determine early-warning capability by looking at lead-time or time-to-event analysis. In principle, the problem of disruption prediction is solved as a probabilistic model of events, where the probability of disruption is calculated with respect to operational, network, and external indicators. This framing permits the comparison of various paradigms of methodology in a single perspective of analysis. The synthesis of the results in these dimensions allows the study to discover methodological strengths and limitations, as well as areas that need additional theoretical and empirical formulation. The systematic analytical methodology that has been used with this review makes it coherent, transparent, and replicable, thus adding to the synthesized knowledge of how machine learning can be used to promote proactive supply-chain disruption management.

According to Figure 3, the suggested conceptual framework will help to combine heterogeneous data inputs, machine learning methods, and operational decision mechanisms into a single predictive framework. The framework starts with three main data sources, namely, operational data that will be obtained based on the enterprise internal systems, network-structural data that will be based on the interdependencies of the suppliers on the multi-tier basis, and external or alternative data that will provide the risk signals due to environmental factors and events. Such inputs are learnt by three different types of machine learning methods, such as supervised learning models, time-series and deep learning architectures, graph-based learning methods, and anomaly detection systems. The data produced through the analysis e.g. disruption risk scores, time to event predictions and early warning systems are actionable data that can be used to guide operational decisions e.g. inventory optimisation, rerouting of logistics, diversity of suppliers and risk mitigation strategies in general. The framework theorizes machine learning as an instrument of predicting, however, only half the pipes, but as a strategic instrument of proactive control of risk in the supply chain.



**Figure 3. Conceptual Framework for Machine Learning–Based Early Prediction of Supply-Chain Disruptions.**

### **Theoretical Grounding: Dynamic Capabilities Perspective**

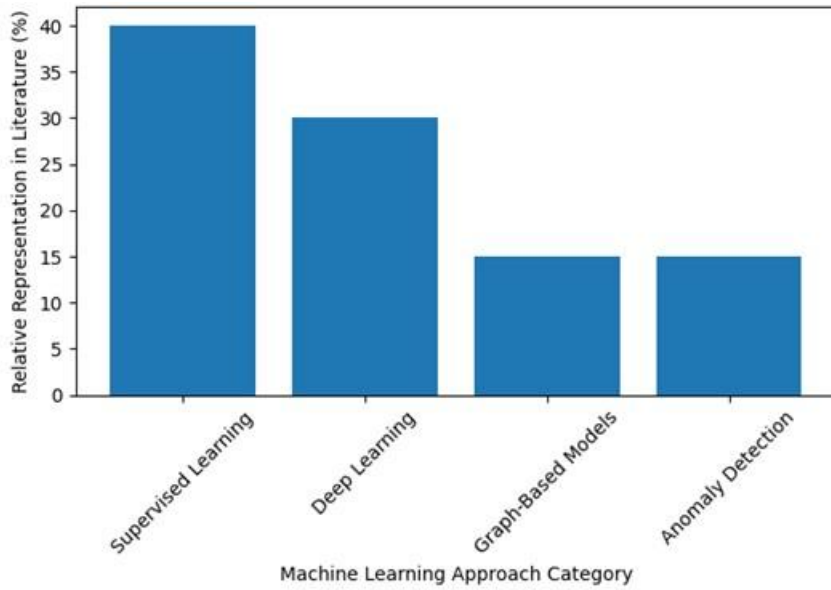
The proposed conceptual framework can be theoretically grounded on the Dynamic Capabilities Theory (Teece, Pisano, and Shuen, 1997; Teece, 2007) that is capable of highlighting the capacity of the firm to sense, seize, and reconfigure the resources to respond to the changing environment in a rapid manner. The supply-chain disruptions are environmental uncertainties that force firms to go beyond a state of the operational efficiency into the capability of active and responsive risk management. In this view, the topmost layer of the framework multidimensional data inputs is related to the sensing ability of the organization. The combination of operational data, network-structural data with the external risk signals boosts the capacity of the firm to identify weak signals and threat in the supply environment. The machine learning techniques capture this sensing capability where the raw data is converted into the warning patterns of the risk, hence reinforcing environmental scanning and early detection of threats. The seizing capability is aided by the support of the second layer-machine learning analytical approaches. Predictive systems can allow firms to screen strategic options and put resources into place by estimating disruption probabilities, time-to-event risks, and anomaly patterns. In lieu of responding to disruptions when they become real, organizations can initiate mitigation measures on the basis of predictive information. Lastly, the connection between the predictive results and operational decision-making indicates the reconfiguring ability. Signals at the initial stage allow making real-time corrections including diversifying suppliers, rerouting logistics, redistributing inventory, and contingency planning. Such activities constitute dynamic reconfiguration of operating resources due to the expectation of disruptions. In this way, the framework conceptualizes machine learning as not a technological solution, but as a facilitator of versatile capabilities that will contribute to the resilience of supply chain and strategic agility. Firms may move towards active and adaptive disruption mitigation by embedding predictive analytics in sensing-seizing-reconfiguring cycle and no longer be reactive risk management.

## **RESULTS**

### **1. General Methodological Trends**

As indicated by the structured review, machine learning applications in the context of supply chain risk continue to be shifted out of traditional predictive analytics and into new, more sophisticated and data-heavy methods. The early literature is dominated by supervised learning models, in particular the ensemble models, like the Random Forest and the Gradient Boosting, which can be interpreted and which are well-suited to structured enterprise data. These models are mainly used in scoring the supplier risks and classifying the operational failures. Recent research evidences a trend towards the increasing use of deep learning systems and more specifically time-series models, specifically Long short-term memory (LSTM) networks. The strategies are of particular interest in the context of disruption prediction where predictive operational cues occur before failure. Nevertheless, as predictive accuracy increases in most instances, the number of studies that specifically assess lead-time performance or early-warning capability is relatively small which encourages the notion of a disconnect between prediction and actionable foresight. Graph-based learning techniques are relatively underrepresented yet have high potential approaches to theory. The research that includes network topology and multi-layer supply relationship suggests.

Supervised learning models are the most popular disruption prediction research methods, as they are utilized in the majority of studies, with deep learning techniques coming in second as illustrated in Figure 4. Graph-based models and anomaly detection systems, in turn, are rather underrepresented, in spite of their possible applicability in interdependency modelling and detection of rare events. This allocation also substantiates the assertion that network mindful and early warning-oriented approaches are not developed in terms of the existing literature.



**Figure 4. Distribution of Machine Learning Approaches in Supply-Chain Disruption Prediction Research**

that structural interdependencies strongly influences disruption propagation. Nonetheless, empirical benchmarking across industries remains limited, and standardized evaluation datasets are lacking (Table 1).

**Table 1. Classification of Machine Learning Approaches Used in Supply-Chain Disruption Prediction**

| Model Category            | Representative Algorithms   | Data Characteristics   | Strengths  | Limitations   | Early-Warning Potential                         |
|---------------------------|---|--|--|---|---|
| Supervised Learning       | Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting | Structured operational datasets with labeled disruption events | Interpretable, stable performance, suitable for tabular ERP data | Limited temporal modeling capability; may ignore network dependencies | Moderate  |
| Time-Series Deep Learning | LSTM, GRU, Temporal CNN   | Sequential operational and logistics time-series data          | Captures temporal dependencies and evolving risk patterns        | Data-intensive; may suffer from rare-event imbalance                  | High (if sequential signals precede disruption) |
| Graph-Based Learning      | Graph Convolutional Networks (GCN), Graph Attention Networks (GAT)            | Multi-tier supplier network and relational data                | Models' disruption propagation across interconnected nodes       | Computational complexity; limited real-world benchmarking             | Potentially High                                |

| Model Category           | Representative Algorithms                     | Data Characteristics                         | Strengths  | Limitations  | Early-Warning Potential |
|--------------------------|---|--|--|--|-------------------------|
| Anomaly Detection Models | Autoencoders, Isolation Forest, One-Class SVM | Unlabeled or weakly labeled operational data | Effective for rare-event detection and early anomaly signals | Higher false-positive rates; interpretability challenges | Early Signal Detection  |

**2. Data Utilization Patterns**

According to the review, most of the studies are based on structured internal operational data with a dominant presence of high-performance indicators of suppliers, inventory variations, and logistical time stamps. Multi-tier network data integration is not as widespread as it is because of data visibility and computation complexity. There are external and replacement data sources, such as news sentiment, environmental signals, and transportation signals, which are also becoming more common, but are still scattered across the literature (Table 2). When integrated, this type of data is more likely to enhance predictive strength, and especially predicting exogenous disturbances, like natural disasters or geopolitical shocks. Systematic multimodal integration is however still at the nascent stage.

**Table 2. Data Categories and Their Role in Disruption Prediction**

| Data Category                 | Typical Examples   | Observed Usage in Literature | Contribution to Prediction                              |
|-------------------------------|--|------------------------------|---|
| Operational Data              | Lead times, order fulfillment rates, shipment delays, supplier performance metrics | High                         | Core predictive signals derived from internal processes |
| Network-Structural Data       | Supplier relationships, tier dependencies, centrality measures                     | Moderate                     | Captures ripple effects and structural vulnerability    |
| External / Environmental Data | Weather events, geopolitical indicators, transportation disruptions                | Low–Moderate                 | Identifies exogenous disruption triggers                |
| Textual / Alternative Data    | News sentiment, public event signals, macroeconomic indicators                     | Low                          | Early detection of emerging risks                       |
| Multimodal Integrated Data    | Combination of operational, network, and external signals                          | Rare                         | Enhances robustness and early-warning accuracy          |

**3. Evaluation Approaches and Early-Warning Capability**

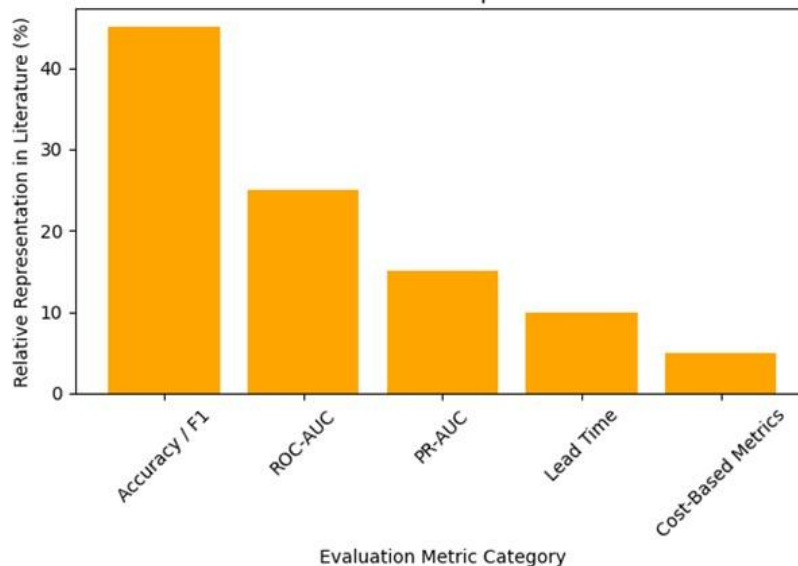
In the literature that has been reviewed, predictive performance is most often evaluated by the standard classification measures of accuracy, precision, recall, and F1-score (Table 3). But even a small number of studies quantify the measure of early-warning effectiveness in terms of lead-time analysis or time-to-event analysis. This observation

implies that prediction disruption studies usually focus on classification performance issues without adequately taking into consideration operational timing issues. In addition, cost-based evaluation metrics that measure trade-offs between false alarms and missed disruptions are not often included. Since early mitigation measures involve economic considerations, the lack of frameworks of utility-based evaluation restricts managerial relevance.

**Table 3. Evaluation Metrics Applied in Machine Learning-Based Disruption Prediction**

| Metric Category                 | Examples   | Frequency of Use | Limitation                                       |
|---------------------------------|--|------------------|--|
| Standard Classification Metrics | Accuracy, Precision, Recall, F1-score, ROC-AUC     | Very High        | Focuses on correctness, not timing               |
| Imbalance-Sensitive Metrics     | PR-AUC, Recall@k                                   | Moderate         | Addresses rare events but not operational timing |
| Time-Based Metrics              | Lead time, detection delay, time-to-event accuracy | Low              | Underutilized despite operational relevance      |
| Cost-Based Metrics              | Expected utility, false alarm cost analysis        | Very Low         | Rarely incorporated into evaluation frameworks   |

As Figure 5 shows, classical classification measures, i.e. accuracy and F1-score, prevail in the practice of evaluation in disruption prediction studies. Even though ROC-AUC and PR-AUC are being used moderately, time-based measurements including the lead time and cost-related assessment schemes are underrepresented considerably. Such imbalance indicates that current studies focus on predictive accuracy at the expense of operational promptness and the cost, thus supporting the research gap identified as the investigation of early-warning capability..



**Figure 5. Evaluation Metrics Used in Machine Learning-Based Disruption Prediction Studies**

**4. Synthesis of Key Findings**

Three key trends can be identified in the review. First, machine learning approaches represent good prospects of modeling the nonlinear and high-dimensional patterns of operational risk. Second, the proposed study area is the network-aware modeling and multimodal data integration, which is an uncertain but promising research direction.

Third, existing literature has not operationalized the notion of early prediction completely, and little attention is paid to the quantifiable benefits of the lead-time.

Overall, the findings suggest that even though sophistication in the methodology of supply chain analytics is becoming more common, the community has not yet agreed on standardized mechanisms of proactive disruptions detection. This makes the case of structured, network aware and lead time oriented predictive systems.

### **DISCUSSION**

The evidence of this systematic review indicates that machine learning has achieved high penetration in the field of supply chain analytics, but its use in providing early warnings about disruptions is still conceptually attractive but methodologically incomplete. The technical feasibility of supervised learning and deep learning models to apply to operational data is already established in current literature, but early-warning capability is seldom a focus of a research problem but often a derived fact. This suggests a critical difference between predictive accuracy and predictive timeliness a point where there is an inadequate literature. Theoretically speaking, the findings support the applicability of the Dynamic Capabilities Theory. Disruption prediction by machine learning can be used to improve the sensing capacity of a firm through the systematically-processed heterogeneous operational and environmental information. However, it is depicted in the literature that there is a little interaction between predictive outputs and adaptive operational reconfiguration. Disruption prediction is discussed in most instances as a technical activity as opposed to an organizational capability cycle that entails sensing, seizing, and reconfiguring. This detachment shows the importance of envisioning predictive analytics as not simply a technical innovation, but as a structural integrative strategic capacity in the framework of supply chain governance.

The other valuable lesson is with regard to network awareness. Supply chains are interdependent systems in which risks are spread out at different levels. Although this is the case, the majority of machine learning solutions still use firm-level data without considering network topology. There is the lack of absorption of graph-based learning techniques which implies that the disruption propagation circumstances are not fully investigated. More emphasis should therefore be given to future work based on structural modeling to realize the ripple effects within multi-layered supplier ecosystems. It is also shown during the discussion that a future research opportunity is the potential of multimodal data integration, which is still uncharted. The increasing supply of alternative information, including news signals, weather information, and transportation signals, offer prospects of earlier identification of exogenous shocks. But systematic implementation has been limited by methodological problems, such as alignment of data, noise cancellation and computational efficiency. It is then vital to develop common frameworks that would combine structured operational data with external risk indicators to enhance proactive risk management.

As a management strategy, the results suggest that organisations must start to transition the emphasis on resilience strategies that are purely reactive, to predictive and preventive strategies. Machine learning is not just valuable in terms of the number of classification performances but also the lead time that it produces to make decisions. The more likely to obtain adaptive resilience are firms that incorporate predictive analytics in the procurement process, logistics planning process, and process of supplier relationship management. Nonetheless, effective execution needs data infrastructure maturity and cross-functional integration and governance mechanisms to respond to predictive signals with the aim of taking actions. In general, the discussion highlights that the conceptualization of early disruption prediction is a dynamic organizational capacity that is nurtured by high-tech analytics. Although the level of methodological sophistication is growing, the discipline has yet to reach a stable protocol to evaluate it, benchmark data and integrative theoretical basis. Overcoming these shortcomings will be necessary in the process of changing experimental machine learning implementation into scalable and strategically embedded early-warning systems.

### **CONCLUSION**

The paper has studied machine learning strategies in the initial forecasting of supply-chain crises and operational risks using a systematic conceptual review. As identified in the analysis, predictive analytics has been gaining greater and greater prominence in the research in the field of supply chain management, but its use in predictive disruption detection remains disseminated and methodologically diverse. The current research reports are characterized by a high level of development of supervised learning and deep learning methods, but little attention has been devoted to the early-warning feature, integration of networks at multiple levels, and multimodal data fusion. The results show

that classification accuracy has been a dominant constraint of disruption prediction research compared to operational timeliness. Not many studies directly measure the benefits of lead-time or use cost-based performance metrics to model the real-world environment of decision making. On the same note, graph-based learning solutions and integration of external data, which is vital in disruption propagation and exogenous risk trigger, are underdeveloped with respect to their potential. This review is based on the Dynamic Capabilities Theory and proposes a conceptualization of machine learning as having enabled organizational sensing, seizing, and reconfiguring capabilities. Predictive systems improve sensing by detecting weak risk indicator through heterogeneous sources of data, aid in seizing through informed risk assessment, and achieve reconfiguration by allowing proactive risk mitigation measures. Therefore, predicting disruptions early should not be considered as an issue concerning only technical modeling, but also as a strategic ability that is integrated into a supply chain governance system. The literature is enhanced in that the study offers a systematic grouping of methodological methods, outlines essential research gaps, and comes up with a comprehensive conceptual model that ties the data inputs, analytical models, and operational decision outputs. This review offers an integrated background to new empirical studies that should be conducted in the future to build standardized, network-sensitive, and lead-time-sensitive disruption prediction systems.

With an ever-changing and globalizing world that has turned into a volatile environment, being able to predict disruptions before they occur is becoming a strategic requirement and not a competitive one. The development of machine learning-based early-warning systems will thus be a key force in the creation of the next generation of resilient and adaptive supply chains.

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