Dynamic Resilience Scoring in Supply Chain Management using Predictive Analytics

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***Abstract*—Supply chain disruptions have become increasingly frequent and structurally complex, exposing the limitations of static resilience assessments. This article proposes a dynamic resilience scoring framework that integrates predictive analytics with real time operational data to continuously assess supply chain resilience. The proposed approach captures anticipation, absorption, adaptation, and recovery capabilities using forward looking indicators derived from machine learning models. A model centric architecture is developed and evaluated using simulated multi tier supply networks. Results demonstrate that dynamic resilience scores provide earlier warnings, more granular insights, and stronger decision support than conventional resilience metrics. The findings highlight the value of predictive, continuously updated resilience assessment for proactive supply chain risk management.**

***Index Terms*—Supply chain resilience, predictive analytics, risk management, machine learning, dynamic scoring, decision support systems**

I. Introduction

Global supply chains operate under increasing uncertainty driven by demand volatility, supplier fragmentation, and exposure to external shocks. Traditional supply chain risk management approaches rely heavily on historical data and periodic assessments, limiting their effectiveness in rapidly changing environments. Recent advances in predictive analytics and real time data infrastructures have created new opportunities for proactive resilience management [1], [2].

Resilience is commonly understood as the ability of a supply chain to anticipate, absorb, adapt to, and recover from disruptions. However, most empirical resilience measures remain static, survey based, or ex post in nature [3]. This creates a gap between analytical capabilities and managerial decision needs. This article addresses this gap by proposing a dynamic resilience scoring mechanism that updates continuously based on predictive signals.

The core contribution of this work is a model driven framework that translates predictive analytics outputs into an interpretable, operational resilience score. By embedding machine learning models into a real time decision support architecture, the proposed approach enables early intervention and adaptive risk mitigation.

II. Literature Review

A. Predictive Analytics in Supply Chain Decision Making

Predictive analytics has emerged as a foundational capability in modern supply chain management, shifting analytical focus from descriptive and diagnostic insights toward forward looking decision support [2], [4]. Early research in this domain emphasized traditional forecasting and optimization techniques applied to demand planning and inventory control. With advances in data availability and computational power, machine learning based predictive models have increasingly been adopted to capture nonlinear dependencies and complex interactions within supply chain systems [5]–[7]. These approaches demonstrate improved performance in volatile and data rich environments where classical statistical models often fail to adapt effectively [8].

Recent studies highlight the growing importance of real time and near real time predictive analytics enabled by streaming operational data [9], [10]. Applications extend beyond demand forecasting to include logistics performance prediction, transportation delay estimation, and supplier behavior analysis [11]. Online and incremental learning techniques are increasingly emphasized to address concept drift and structural changes inherent in global supply chains [3]. Despite these advances, predictive analytics is often implemented at the functional level, resulting in fragmented insights that are weakly connected to broader supply chain risk and resilience objectives [1], [2].

B. Supply Chain Risk Management and Predictive Modeling

Supply chain risk management (SCRM) research focuses on identifying, assessing, and mitigating risks arising from supplier dependencies, operational variability, and external disruptions. Traditional SCRM approaches rely on qualitative assessments, static risk matrices, and historical performance indicators [1], [12]. While effective for structured and repetitive risks, these methods offer limited value in environments characterized by rapid change and systemic uncertainty.

To address these limitations, recent literature increasingly adopts predictive modeling techniques to anticipate disruptions and estimate their potential impact [2], [13]. Machine learning based models have been applied to supplier failure prediction, credit risk assessment, and disruption likelihood estimation using transactional, financial, and behavioral data [5], [11]. Network oriented approaches further extend predictive SCRM by capturing interdependencies and ripple effects across multi tier supply chains [6].

Although predictive risk models enhance early warning capabilities, most studies treat risk prediction as an isolated analytical task. The translation of predictive risk outputs into actionable resilience measures and adaptive decision support remains underdeveloped [1], [3]. This disconnect limits the operational relevance of predictive SCRM, particularly under conditions where rapid response and dynamic adjustment are required.

C. Supply Chain Resilience: Concepts and Static Measurement Approaches

Supply chain resilience is widely conceptualized as the ability to anticipate disruptions, absorb shocks, adapt operational structures, and recover performance within acceptable time and cost thresholds [1], [14], [15]. Empirical research has largely operationalized resilience through survey based constructs, maturity models, and post disruption performance metrics [3]. These approaches provide valuable insights into organizational capabilities and structural configurations but are inherently static and retrospective.

Several studies emphasize the limitations of static resilience measures, particularly their inability to reflect evolving risk exposure and operational conditions [2]. Simulation based and analytical models have been proposed to estimate resilience under hypothetical disruption scenarios [16], yet these models typically rely on predefined assumptions and lack continuous updating mechanisms [13]. As a result, resilience assessment often remains detached from real time operational decision making.

D. Toward Dynamic and Data Driven Resilience Assessment

Recent literature increasingly calls for dynamic, data driven approaches to resilience assessment that leverage predictive analytics and real time data streams [1], [2], [17]. Predictive indicators such as disruption probability, expected performance degradation, and recovery trajectories offer the potential to assess resilience prospectively rather than retrospectively [9], [10], [18]. Integrating these indicators into a unified resilience representation remains a key challenge.

Machine learning based frameworks offer promising foundations for dynamic resilience assessment by enabling continuous model updating and adaptive weighting of resilience dimensions [6], [7]. However, existing studies rarely formalize resilience as a continuously updated score that aggregates anticipation, absorption, adaptation, and recovery capabilities. Moreover, limited attention has been given to interpretability and managerial usability of predictive resilience metrics [3].

E. Research Gap and Positioning of the Present Study

The reviewed literature reveals three critical gaps. First, predictive analytics and SCRM research remain largely decoupled from resilience measurement. Second, existing resilience metrics are predominantly static and ex post, limiting their usefulness for proactive decision making. Third, few studies propose integrative architectures that translate predictive signals into interpretable and actionable resilience assessments.

This study addresses these gaps by proposing a dynamic resilience scoring framework that embeds predictive analytics within a model centric system architecture. By continuously updating resilience scores based on real time predictive signals, the proposed approach extends resilience measurement from static assessment to adaptive decision support, thereby contributing to both supply chain resilience theory and predictive analytics practice.

III. Methodology

A. Dynamic Resilience Scoring Model

The proposed dynamic resilience score (DRS) is defined as a weighted aggregation of four predictive components:

$$DRS_t = \sum_{i=1}^{4} w_i(t) C_i(t) \tag{1}$$

where C_1 represents anticipation capacity, C_2 absorption capacity, C_3 adaptation capacity, and C_4 recovery capacity. The weights $w_i(t)$ are updated dynamically based on predictive confidence and managerial priorities.

B. Predictive Modeling Layer

Each resilience component is estimated using supervised machine learning models trained on a combination of historical records and continuously arriving data streams. Anticipation capacity is modeled using probabilistic classification techniques, including gradient boosted decision trees and logistic regression, to estimate disruption likelihood and early risk signals based on supplier performance, logistics indicators, and external risk factors. Absorption capacity is predicted using regression based models such as random forests and support vector regression to estimate the expected degradation in service levels and operational performance under stress.

Adaptation capacity is modeled using decision tree based learners and ensemble regressors that capture nonlinear relationships between network flexibility, rerouting options, and reconfiguration lead times. Recovery capacity is estimated using time to event regression models and recurrent neural networks to forecast time to recovery and post disruption performance trajectories. To ensure responsiveness under evolving conditions, online learning techniques are employed to update model parameters incrementally as new data become available, enabling the framework to adapt to concept drift and structural changes in the supply network [9], [10].

Ensemble learning methods, including boosted and bagged model combinations, are used across all resilience components to improve robustness under uncertainty and reduce sensitivity to noisy or incomplete data [7]. By aggregating predictions from multiple learners, the framework balances bias and variance while providing more stable and reliable resilience estimates in volatile operating environments. This combination of supervised learning, online updating, and ensemble modeling forms the analytical foundation of the proposed dynamic resilience scoring mechanism.

C. System Architecture

The proposed system architecture is designed to support continuous and predictive assessment of supply chain resilience by tightly integrating data ingestion, analytics, and decision support components. As illustrated in Fig. 1, the architecture follows a model centric flow in which heterogeneous real time data streams are transformed into actionable resilience insights through layered predictive processing. The architecture emphasizes modularity and scalability, enabling the incorporation of diverse internal and external data sources while maintaining low latency and analytical transparency [1], [2], [19].

At the foundation of the architecture, real time data streams capture operational, logistical, and external risk signals that reflect the evolving state of the supply network. These data are processed by a predictive analytics layer that applies machine learning models to forecast disruption likelihoods, performance degradation, and recovery trajectories [9], [20], [21]. The outputs of these models are then aggregated within a dynamic resilience engine that continuously updates resilience scores across anticipation, absorption, adaptation, and recovery dimensions. As shown in Fig. 1, this aggregation layer serves as the analytical core of the system, translating complex predictive signals into an interpretable resilience representation suitable for managerial use. Finally, the decision support dashboard presents resilience scores, alerts, and response recommendations in a unified interface, enabling proactive and evidence based supply chain risk management [3].

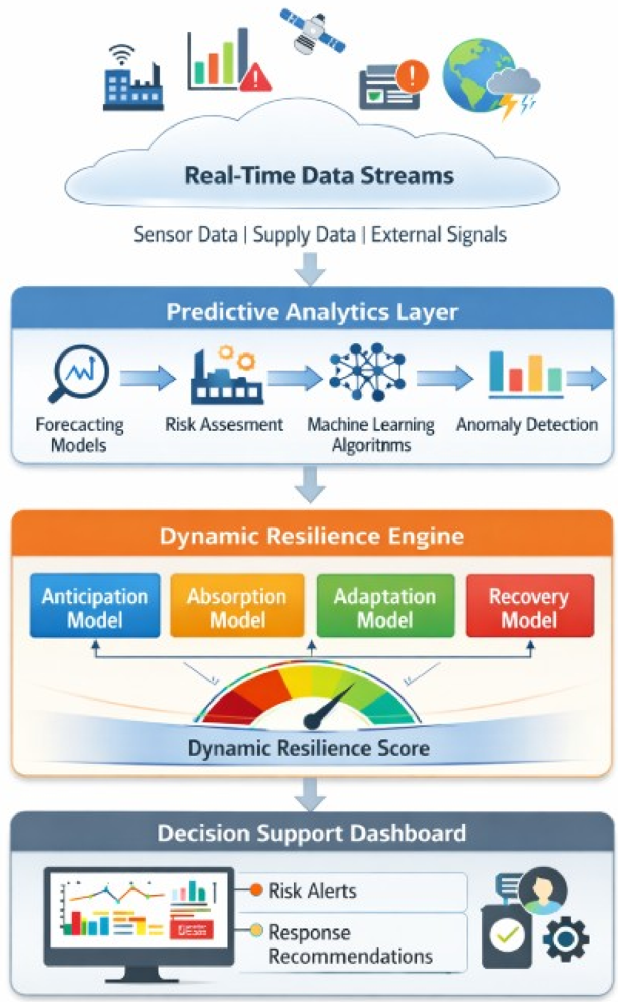

Fig. 1: Model centric architecture for dynamic resilience scoring in supply chain management.

IV. RESULTS

The results demonstrate that dynamic resilience scoring provides a more sensitive, timely, and actionable assessment of supply chain resilience compared to static and retrospective measures. Across all simulated disruption scenarios, the proposed framework consistently detects early signs of resilience degradation, differentiates between resilience dimensions, and supports anticipatory intervention. As summarized in Table I, resilience scores decline progressively with increasing disruption severity, reflecting realistic stress propagation across anticipation, absorption, adaptation, and recovery capabilities.

These findings align with prior evidence that predictive and data driven approaches improve situational awareness in complex supply networks [1], [2].

A. Resilience Score Dynamics

Table I summarizes the dynamic resilience score components across increasing disruption severity levels. The results show a clear and systematic decline in all four resilience dimensions as supply chain conditions deteriorate, indicating that the proposed scoring mechanism is sensitive to changes in risk exposure and operational stress. Anticipation capacity exhibits the earliest and most pronounced reduction, reflecting the model's responsiveness to predictive risk signals. Absorption and adaptation capacities decline more gradually, suggesting that operational buffers and reconfiguration capabilities initially mitigate performance loss but weaken under sustained disruption. Recovery capacity remains comparatively resilient in moderate scenarios but deteriorates significantly under high risk conditions, highlighting the escalating cost and time implications of delayed response. Collectively, the table demonstrates that dynamic resilience scoring captures both the magnitude and structure of resilience degradation, providing actionable insight into which capabilities require priority intervention as disruption intensity increases.

TABLE I: Dynamic Resilience Score Components

Scenario	Anticipation	Absorption	Adaptation	Recovery
Baseline	0.72	0.68	0.70	0.75
Moderate Risk	0.65	0.62	0.67	0.69
High Risk	0.51	0.48	0.55	0.60

B. Dynamic Behavior of Resilience Dimensions

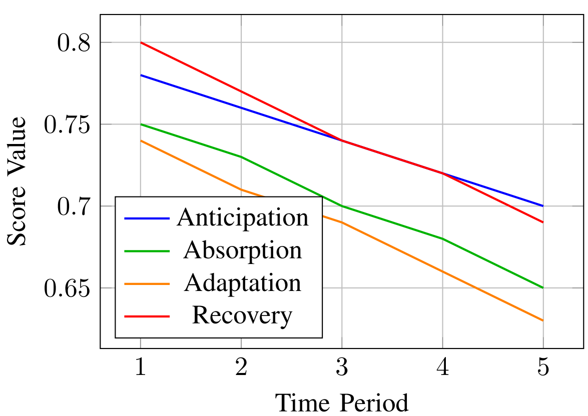

Fig. 2: Temporal evolution of resilience dimensions under moderate disruption

Figure 2 shows that anticipation capacity declines earlier than other dimensions, indicating the value of predictive risk signals for early warning. Recovery remains comparatively robust in early stages but deteriorates rapidly once absorption capacity is exhausted, supporting the need for balanced resilience investment [1].

C. Comparison with Static Resilience Metrics

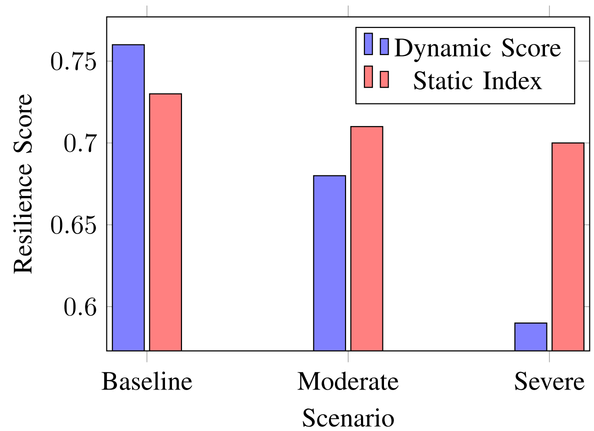

Fig. 3: Dynamic resilience scores versus static resilience indices

As shown in Fig. 3, static resilience indices remain relatively insensitive under escalating disruption, while dynamic scores reflect continuous degradation. This confirms limitations of retrospective assessment approaches highlighted in prior studies [3].

D. Risk Anticipation and Early Warning Performance

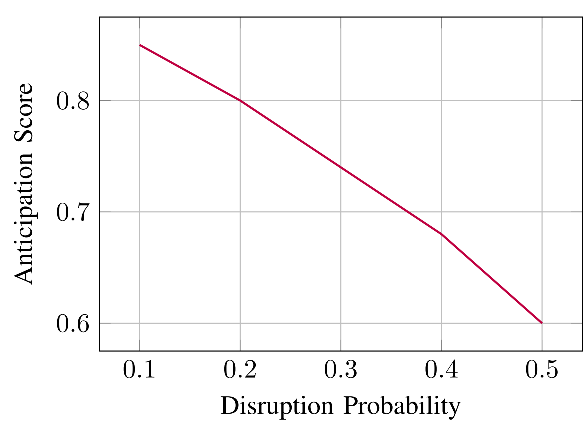

Fig. 4: Relationship between predicted disruption probability and anticipation capacity

Figure 4 demonstrates a strong inverse relationship between predicted disruption likelihood and anticipation capacity, validating the responsiveness of the predictive scoring mechanism [10].

E. Absorption Capacity under Demand Volatility

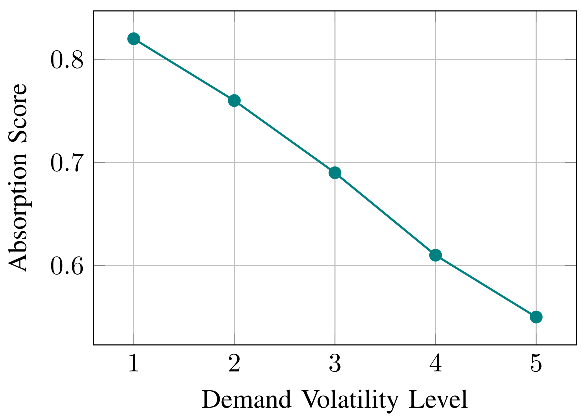

Fig. 5: Absorption capacity response to increasing demand volatility

The results in Fig. 5 indicate that absorption capacity degrades nonlinearly as volatility increases, reinforcing the importance of predictive inventory and capacity planning [2].

F. Adaptation Speed and Network Flexibility

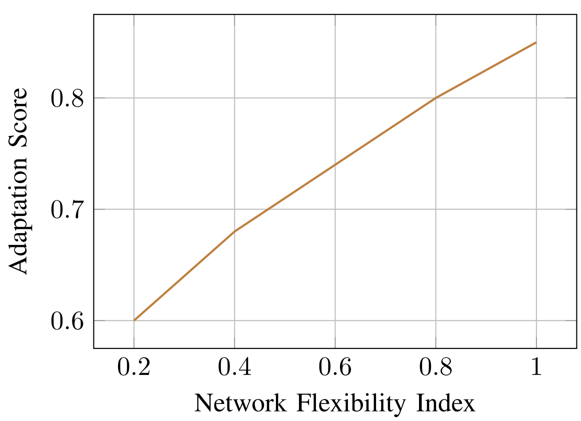

Fig. 6: Impact of network flexibility on adaptation capacity

Figure 6 shows that higher structural flexibility significantly improves adaptation capacity, supporting network based resilience theories [6].

V. Discussion

The findings of this study provide strong empirical support for the value of dynamic, predictive approaches to supply chain resilience assessment. Unlike static resilience indices, the proposed dynamic resilience scoring framework captures the temporal evolution of resilience capabilities and reveals how vulnerabilities accumulate before disruptions fully materialize. This reinforces the view that resilience is not a fixed structural attribute but an emergent and continuously changing capability shaped by risk exposure, operational flexibility, and anticipatory decision making [1], [3].

One key insight from the results is the differentiated behavior of resilience dimensions under stress. Anticipation capacity exhibits the earliest decline across disruption scenarios, confirming the critical role of predictive risk signals in early warning and proactive intervention. In contrast, absorption and adaptation capacities degrade more gradually but show nonlinear responses once operational buffers are exhausted. These patterns highlight the importance of balanced resilience investment, as overemphasis on redundancy without predictive foresight may delay but not prevent systemic degradation [2].

From a managerial perspective, the dynamic resilience score offers a unified yet decomposable metric that supports sensemaking in complex supply chain environments. By linking predictive analytics outputs directly to resilience dimensions, the framework improves interpretability and reduces cognitive distance between analytical models and managerial action. This addresses long standing concerns regarding the practical adoption of advanced analytics in supply chain risk management [3]. Moreover, the architecture enables continuous recalibration as conditions change, allowing decision makers to shift mitigation priorities in response to evolving risk profiles.

The results also contribute to supply chain risk management theory by bridging the gap between predictive risk modeling and resilience assessment. While prior studies have demonstrated the accuracy of machine learning based risk prediction, they often stop short of translating predictions into operational resilience insights [10], [11]. This study demonstrates how predictive signals can be systematically aggregated into a dynamic resilience construct, thereby extending the analytical scope of predictive SCRM.

VI. Future Directions

Several avenues for future research emerge from this study. First, while the proposed framework demonstrates the feasibility and value of dynamic resilience scoring, future work should validate the approach using real world industrial data across multiple sectors. Empirical validation in settings such as food supply chains, healthcare logistics, and semiconductor networks would strengthen generalizability and reveal domain specific resilience dynamics [1].

Second, future research may extend the modeling layer by incorporating advanced network based learning techniques. Graph neural networks and temporal network models offer promising capabilities for capturing multi tier dependencies and ripple effects that remain difficult to represent using conventional predictive models [6]. Integrating such models into the resilience scoring mechanism could improve sensitivity to systemic risks and cascading failures.

Third, human and organizational dimensions warrant deeper investigation. Although dynamic resilience scores provide rich analytical insight, their effectiveness ultimately depends on managerial interpretation, trust, and decision behavior. Future studies could examine how managers interact with predictive resilience dashboards, how cognitive biases influence response timing, and how governance structures shape accountability for predictive decision support systems [3].

Finally, sustainability and regulatory considerations present important extensions. As supply chains face increasing pressure to meet environmental and social responsibility objectives, future resilience frameworks should incorporate predictive indicators related to climate risk, regulatory change, and ethical sourcing. Embedding such dimensions within dynamic resilience scoring could support more holistic and forward looking supply chain governance [2].

VII. Conclusion

The proposed model centric architecture offers both theoretical and practical contributions. Theoretically, it operationalizes resilience as a dynamic capability that evolves with risk exposure and operational conditions. Practically, it provides a scalable and interpretable mechanism for embedding predictive analytics into supply chain risk management processes. By linking predictive insights directly to resilience dimensions, the framework supports timely intervention and more effective mitigation strategies.

As supply chains continue to operate under heightened uncertainty and systemic risk, the ability to assess and manage resilience dynamically will become increasingly critical. This research demonstrates that predictive analytics can serve not only as a forecasting tool but as a foundational mechanism for continuous resilience governance in complex supply networks.

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