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| RESEARCH ARTICLE

AI-Driven Resilient Supply Chain Architectures: Machine Learning Frameworks for Risk Anticipation, Disruption Mitigation, and Adaptive Decision-Making

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| ABSTRACT

Global supply chains face various disruptions related to demand volatility, geopolitical tensions, weather-related disruptions, and operational failures, making conventional rule-based and reactive resilience approaches inadequate for addressing these disruptions. Recent developments in artificial intelligence (AI) and machine learning (ML) offer promising opportunities for transforming supply chain resilience from conventional reactive approaches to proactive, adaptive, and learning-enabled decision-making systems. However, the prevailing literature primarily focuses on standalone AI-related activities without discussing the architectural aspects of integrating AI for end-to-end supply chain resilience under uncertainty. This study proposes a unified resilient supply chain architecture with the incorporation of machine learning technologies in the processes of anticipation, mitigation, and adaptive decision-making. The research methodology used in the study is the design science research approach, which resulted in the development of a multi-layered framework consisting of the data intelligence layer, the risk anticipation layer, the prescriptive decision and mitigation layer, and the adaptive learning feedback layer. The framework ensures the integration of various machine learning algorithms with supervised learning, unsupervised learning, and reinforcement learning techniques with various categories of supply chain risks. In order to test the theoretical robustness of the proposed architecture, a scenario-based evaluation approach is followed, and various disruption scenarios, which cover failures from the suppliers, disruptions in the logistics network, and demand disruptions, are analyzed. New evaluation criteria, which are classified under the term "resilience-oriented evaluation," are also proposed in the paper, which move beyond the traditional evaluation criteria of costs and services. This paper contributes to the literature in the fields of supply chain and operations management, as an integrative AI architecture for building resilience is proposed, and the conceptualization of adaptive supply chains is advanced, while also providing guidance for managers and policymakers who are interested in leveraging AI as a strategic tool for building resilience in an ever-increasingly volatile environment.

| KEYWORDS

Supply Chain Resilience, Machine Learning, Disruption Mitigation Frameworks, Intelligent Supply Chain Architectures

| ARTICLE INFORMATION

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1. Introduction

Global supply chains are embedded in an environment that is marked by continuous and systemic disruption. The recent disruptions, including the pandemic-induced demand shocks, geopolitical tensions, climate-change-related logistics disruptions, insolvencies, and cyber-physical disruptions, have highlighted the systemic issues in the global supply chain. The disruptions are no longer episodic or isolated; rather, they have become the new normal. The disruptions are embedded in the supply chain environments. In this context, the traditional supply chain risk management practices, which are largely static in nature, relying on risk registers, contingency planning, and human decision cycles, have failed to ensure the continued operation of supply chains.

Traditionally, supply chain resilience has focused on supply chain robustness, achieved via supply chain redundancies, safety stock, and dual sourcing. Although these provide a degree of short-term supply chain resilience, they are fundamentally reactive and costly, and they cannot dynamically adapt to changing supply chain risk. Moreover, rule-based decision systems also struggle to scale across complex supply chains where disruptions spread non-linearly and where early warning signs of disruptions often originate from unstructured and heterogeneous data sources. As a result, supply chain disruptions are typically only addressed once significant performance degradation has been realized, resulting in longer supply chain recovery periods and increased economic loss [1].

The recent advancements in artificial intelligence (AI) and machine learning (ML) have provided new opportunities to rethink the concept of supply chain resilience as an adaptive and data-driven concept, rather than a static and defensive concept. Machine learning methods, such as predictive analytics, anomaly detection, and decision optimization through reinforcement learning, can provide the ability to continuously sense risk signals, probabilistically predict disruptions, and dynamically select mitigation actions in the face of uncertainty. When compared to traditional decision-support systems, AI-driven methods can leverage past disruptions to improve decision-making and respond at speeds that are beyond the reach of traditional human-only coordinating mechanisms. In this regard, AI can play the role of a fundamental enabler of future supply chain resilience architectures [2].

However, despite the potential of the field, the body of existing research on the topic of AI in SCM is still scattered. The earlier research has mostly focused on individual applications of AI in SCM, for example, in demand forecasting, inventory optimization, supplier risk scoring, or transportation planning. While the contributions of the earlier research are valuable in their own right, the question of how a range of AI technologies can be meaningfully integrated into an end-to-end architectural framework for resilience management across the entire disruption lifecycle, from early risk anticipation to mitigation execution and learning after a disruption, has received little attention. In addition, little attention has been paid to the question of how the resilience performance of a supply chain can be adapted via feedback [3].

This research intends to fill these gaps by proposing a unified resilient supply chain architecture that leverages AI technologies for machine learning. This research follows a design science research approach and proposes a layered architecture that provides a systematic mapping of supervised, unsupervised, and reinforcement learning paradigms to different types of supply chain risks. This proposed architecture highlights closed-loop learning, human-AI collaboration, and resilience-based performance measures, which can help supply chains transform from response-based supply chains to intelligent and adapting supply chains.

The contributions of the present study can be identified at four different levels. First, the study contributes to the concept of resilience in the SC domain. For this purpose, the study has proposed an architecture-level framework for AI. Second, the study has proposed a structured mapping between machine learning paradigms and SC risks. This provides a basis for the practical application of AI in uncertain environments. Third, the study has proposed a set of metrics for the evaluation of the resilience of SC systems. Last, the study has some implications for the practical application of AI systems in SC systems.

The outline for the rest of this paper is as follows: Section 2 discusses the conceptual foundations and existing body of knowledge on supply chain resilience and artificial intelligence. Section 3 discusses the research methodology and development of the analytical framework. Section 4 presents the proposed architecture for artificial intelligence-based supply chain resilience. Section 5 presents the machine learning framework for adaptive decision-making. Section 6 presents the evaluation criteria for supply chain resilience. Section 7 presents the managerial and policy implications. Section 8 presents the limitations and future directions for research.

2. Conceptual Foundations and Related Work

2.1 Supply Chain Resilience: From Robustness to Adaptive Capability

Supply chain resilience has been traditionally defined as the capability of the supply chain system to resist, absorb, and recover from supply chain disruptions while maintaining acceptable performance levels. Initial supply chain resilience approaches emphasized the importance of robustness, as exemplified by structural supply chain resilience mechanisms such as safety stock, redundant supply chain capacity, and multiple sourcing. Although such mechanisms are helpful in reducing the susceptibility of supply chain systems to certain types of supply chain disruptions, these are by their very nature static, economically inefficient, especially in environments characterized by high levels of uncertainty, as well as presupposing certain levels of supply chain risk stability, which is becoming increasingly inappropriate given the volatile global business environment [4].

Recent views have expanded the definition of resilience from simply robustness to incorporate the attributes of agility and flexibility. These views of resilience accept that disruptions spread dynamically throughout complex supply networks, requiring timely decision-making across numerous nodes and tiers. However, even these sophisticated views of resilience, which focus on response and reconfiguration, have been found to struggle in scaling to increased complexity, adapting to unknown disruptions, and leveraging subtle signals within large volumes of diverse data. This limitation has led to the development of a view of resilience that considers it no longer simply a structural attribute but a dynamic and learning-based attribute [5].

From this perspective, adaptive resilience refers to a supply chain's ability to continually sense changes in its environment, anticipate emerging risks, and modify its response strategies based on feedback from previously experienced disruption events. Achieving such adaptivity requires decision-making systems that can process high-dimensional information, learn complex nonlinear relationships, and adapt under uncertain conditions—all beyond the limits of conventional analysis and decision-making. Such a progression in thinking around supply chain resilience can provide a natural theoretical basis for integrating AI and ML into supply chain design [6].

2.2 Artificial Intelligence and Machine Learning in Supply Chain Management

Artificial intelligence and machine learning have increasingly been incorporated as part of supply chain management with the aim of improving accuracy in forecasting, efficiency in operations, and decision-making. The literature has been grouped into three main categories: predictive, descriptive, and prescriptive. In predictive supply chain management, supervised learning algorithms have been utilized for forecasting demand, determining lead times, and assessing reliability. In descriptive supply chain management, data analytics has been used for improving supply chain visibility. Prescriptive supply chain management has been achieved through optimization and heuristic methods [7].

More recently, for example, unsupervised machine learning methods such as clustering and anomaly detection have been used for discovering hidden patterns and detecting unusual operational behaviors, and reinforcement learning has been studied for sequential decision problems related to inventory control and pricing. These advances demonstrate the promise that machine learning may hold for enabling complex supply chain decisions under uncertainty. The great majority of applications remain functionally segregated and focused on local optima [8].

One of the notable limitations of the current literature is the absence of unifying frameworks that integrate data ingestion, risk prediction, decision execution, and learning feedback under a single architectural umbrella. There are many studies that treat AI models as autonomous tools that operate within their respective silos of application, such as demand planning or transportation management. Consequently, the information that these models generate remains inaccessible within the wider supply chain decision environment, thereby limiting the ability to forecast disruption cascades or coordinate mitigation responses. Furthermore, only a few studies address the issue of how AI systems should revise their decision logic in response to disruption events, which remains a necessary prerequisite for resilience in dynamic environments [9].

2.3 Research Gaps and Motivation for an Architectural Perspective

Yet, despite the increasing number of research works on AI-based SC applications, there are still significant gaps to be addressed. First, the emphasis is not put on the anticipation of risks, and most research works focus more on the response to disruptions or the optimization of efficiency. Second, the current AI-based SC applications do not support the closed-loop learning needed to update the decision policies based on the observed outcomes. Third, the current literature has not offered much information regarding the integration of various machine learning approaches, such as supervised learning, unsupervised learning, and reinforcement learning, to deal with various types of SC risks in a holistic manner [10][11][12].

These gaps, therefore, underscore the need for an architecture-oriented approach that moves beyond individual AI applications and pushes forward a more holistic approach to the development of intelligent and resilient supply chains. The architecture, therefore, must facilitate continuous data fusion from diverse sources, probabilistic risk predictions, dynamic decision-making, and learning. It must also facilitate effective human-AI collaboration through the provision of transparency and interpretability in decision-making.

In addressing these challenges, this study proposes an AI-enabled resilient supply chain architecture that incorporates machine learning throughout the entire disruption life cycle. This architecture is built on existing resilience theory, but incorporates adaptive learning mechanisms to overcome the limitations of the existing literature, providing the foundation for the next generation of supply chain resilience.

3. Research Methodology

3.1 Methodological Approach

In this study, the Design Science Research (DSR) approach is used to develop and evaluate the AI-based resilient SC architecture. The use of the Design Science Research approach is justified due to the nature of the problem, which is complex and socio-technical, and the objective of the research, which is to develop and rationalize new artifacts such as architectures, frameworks, and decision models, addressing gaps in existing theory and practice. In the SC resilience problem domain, the use of the Design Science Research approach is justified due to its ability to facilitate the translation of theoretical contributions and emerging AI technology into decision support, which is adaptable and can accommodate uncertainty.

The methodological decision is informed by two primary considerations. First, the problem under investigation is inherently architectural, requiring the integration of disparate data sources, machine learning, and decision-making at various tiers of the supply chain. Second, the availability of empirical data regarding large-scale, disruption-driven SC disruptions is often limited or unavailable, making a theory-driven approach to artifact development and validation a viable and acceptable solution in the fields of OM and IS. The use of existing resilience theory and machine learning paradigms ensures the proposed framework is both theoretically sound and relevant.

3.2 Research Design and Framework Development

The research design follows a structured, multi-stage process consistent with established design science guidelines.

Stage 1: Problem Identification and Risk Characterization

This first step involves the identification of the limitations associated with traditional methods of supply chain resilience through the integration of existing literature. Supply chain risks are broadly categorized as demand-side risks, supply-side risks, operational risks, and systemic risks. This provides the basis upon which various types of risks are mapped to various machine learning techniques.

Stage 2: Mapping of Machine Learning Capabilities

In this step, the machine learning paradigms are mapped to the identified risk category types based on the strengths of the analysis. Supervised learning methods are mapped to predictive analysis, including demand volatility estimation and supplier performance forecasting. Unsupervised learning methods are mapped to anomaly detection and the identification of new, unknown disruption patterns. Reinforcement learning is mapped as the primary means through which adaptive policy selection is carried out. This ensures that the proposed architecture benefits from multiple machine learning capabilities rather than using a single analysis method.

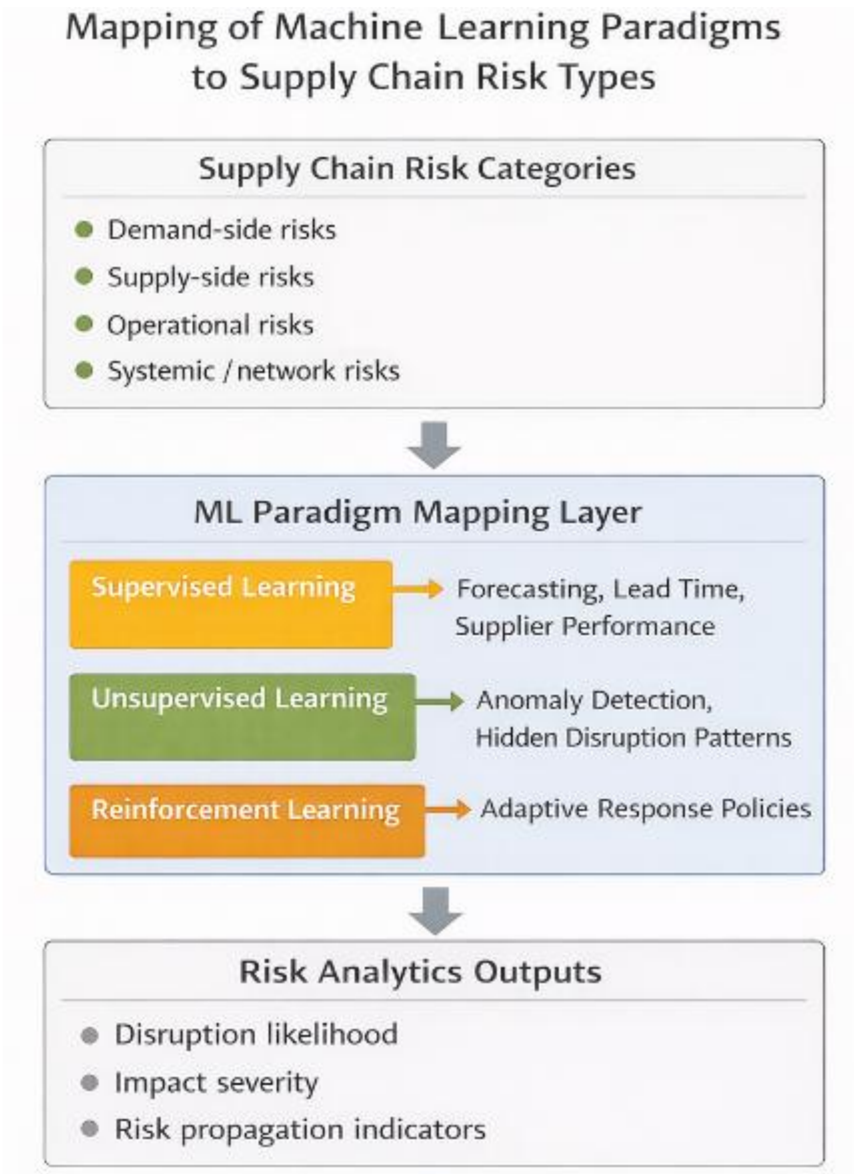

Fig 1. Supply chain risk categories

The above fig illustrates the mapping of various categories of supply chain risks (demand risks, supply risks, operating risks, and system risks) with various paradigms of machine learning. Here, supervised learning is used for forecasting and predicting supplier performance. Unsupervised learning is used for anomaly detection and revealing hidden patterns of supply chain disruptions. Reinforcement learning is used for deriving response strategies. All these results in various forms of supply chain risk analytics.

Stage 3: Architectural Synthesis.

In the third stage, the data, analytics, and decision components are synthesized within a layered, AI-enabled, resilient SC architecture. This architecture is designed to support the continuous ingestion of data, probabilistic anticipation of risks, mitigation of risks in a dynamic manner, and learning through feedback. Specific focus is given to the closed-loop learning processes that can be employed to update decision policies in response to disruption events, which is a key differentiator in comparison to traditional decision support systems.

3.3 Evaluation Strategy

In consideration of the conceptual orientation of the proposed framework, this research applies scenario-based evaluation as a method for evaluating the theoretical robustness as well as the applicability of the architecture under consideration. Scenario-based evaluation is one of the most commonly used methods for evaluating systems, particularly in resilience research, without relying on proprietary data sets. The scenarios considered for this research include disruptions related to suppliers, disruptions related to the logistics network, disruptions related to customer demand, as well as disruptions related to data integrity.

In order to support the proposed analysis of the scenario, this research also introduces a set of resilience-oriented evaluation criteria, which transcend the traditional criteria of efficiency. The criteria proposed are time to recovery, speed of adaptation, decision latency, and learning efficiency. The analysis of the system with regard to the proposed criteria helps the research provide a basis to compare AI-based resilient systems with traditional, rule-based approaches to managing the supply chain.

3.4 Methodological Rigor and Validity

The methodological quality of the present research is ensured via alignment with the principles of established design science research, traceability of the research process from problem definition to artifact design, and the explicit justification of the underlying modeling assumptions. Despite the fact that the empirical validation of the framework is beyond the present research focus, the proposed framework has been developed in a manner that makes it easily implementable in the course of the forthcoming empirical research. Therefore, the methodology can be seen as a foundational contribution to the emerging field of AI-supported SC resilience.

4. Proposed AI-Driven Resilient Supply Chain Architecture

This section proposes a unified AI-based resilient supply chain architecture that can potentially support proactive risk anticipation, dynamic disruption mitigation, and adaptive decision-making in the context of uncertainty. Unlike traditional decision support systems that operate within their respective silos, this proposed architecture integrates machine learning throughout the disruption life cycle via a layered and modular approach. Moreover, this architecture specifically highlights the importance of closed-loop learning, system-wide coordination, and human-AI collaboration, which can potentially transform supply chains from reactive response systems into intelligent systems that can learn and adapt.

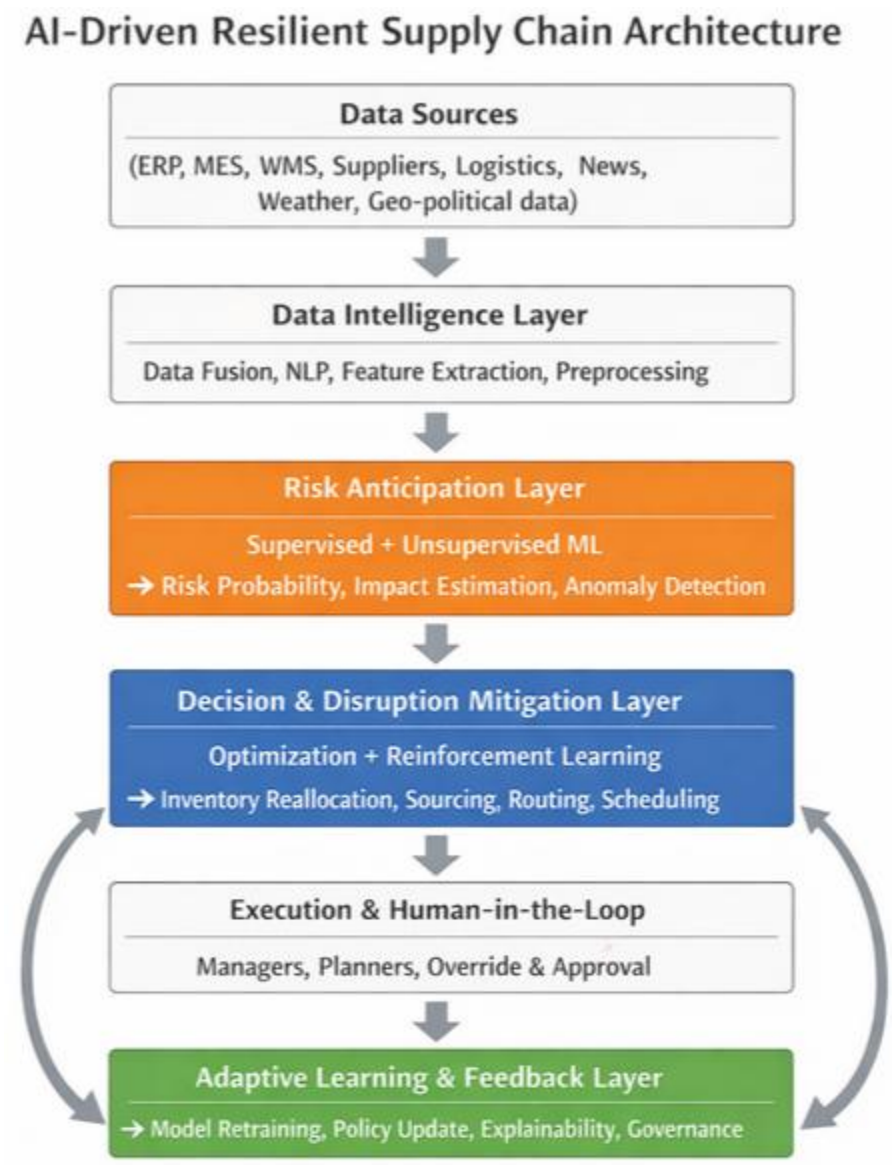

Fig 2. AI-driven layered supply chain architecture

The above figure represents an AI-based layered supply chain model where multi-source data is transformed into risk predictions using machine learning models. These predicted risks are further transformed into risk mitigation decisions using optimization and reinforcement learning techniques, and managerial personnel are also included during the execution of this model to produce desired outcomes, which are further used to retrain the model to achieve adaptive resilience.

4.1 Architectural Overview

The proposed architecture includes four layers: (1) the Data Intelligence Layer, (2) the Risk Anticipation Layer, (3) the Decision and Disruption Mitigation Layer, and (4) the Adaptive Learning and Feedback Layer. Each layer is designed to perform one specific function while continuously interacting with the other layers, thus closing the loop for the decision process. The proposed architecture is hierarchical in nature, thus allowing the integration of artificial intelligence without the need for re-designing the existing organizational systems.

At the system level, the system design aligns with a sense-predict-decide-act-learn paradigm. Data streams are continuously ingested from internal and external sources and converted into actionable intelligence, which is then processed by predictive and prescriptive machine learning models that aid in the formulation of mitigation decisions. The outcome of executed decisions is fed back into the system for continuous improvement of resilience performance.

4.2 Data Intelligence Layer

The Data Intelligence Layer is the foundational layer of the architecture because it facilitates end-to-end visibility across the supply chain ecosystem. It combines structured data from enterprise systems, including enterprise resource planning systems, manufacturing execution systems, and warehouse management systems, with unstructured and semi-structured data from communications with suppliers, logistics providers, news feeds, weather services, and geopolitical risk indicators.

The machine learning models used in this layer of the architecture focus on data fusion, feature extraction, and noise reduction. The natural language processing models transform unstructured data into risk signals, while the data preprocessing models transform heterogeneous data into a common format for subsequent analytics. The aggregation of heterogeneous data streams in the Data Intelligence Layer ensures that weak signals of potential disruption are identified in time for risk anticipation in subsequent layers.

4.3 Risk Anticipation Layer

The role of the Risk Anticipation Layer is the identification of risks that are emerging in the system, along with the likelihood and possible impact of the disrupting event. It uses supervised and unsupervised machine learning for addressing the uncertainty in the system. Supervised machine learning models are used for predicting the demand volatility, lead time variability, and supplier performance degradation using the historical patterns. Unsupervised machine learning models, on the other hand, are used for detecting the anomalous behaviors in the system. The supervised machine learning models provide the predictions for the demand volatility, lead time variability, and supplier performance degradation. Unsupervised machine learning models provide the predictions for the demand volatility, lead time variability, and supplier performance degradation. It is noteworthy that the predictions made in the Risk Anticipation Layer are continuously updated in real time in accordance with the changing patterns of the supply chain environment.

4.4 Decision and Disruption Mitigation Layer

The Decision and Disruption Mitigation Layer translate the identified risks into actionable response strategies. This layer includes prescriptive analytics, optimization techniques, as well as reinforcement learning that enables the assessment of various mitigation actions under uncertain situations. The decisions that are made involve various actions like inventory re-allocation, supplier switching, production rescheduling, as well as transportation re-routing.

The reinforcement learning agents play a central role in this layer as they seek adaptive decision policies through interactions with the supply chain environment. By analyzing the outcomes of previously executed actions, they seek to strike a balance between short-term operational efficiency as well as long-term resilience. The structure also supports decision execution as well as human-in-the-loop intervention, allowing decision-makers to override actions with their own knowledge as well as considerations.

4.5 Adaptive Learning and Feedback Layer

The Adaptive Learning and Feedback Layer distinguishes between resilient AI systems and fixed decision support systems. This layer monitors the results of system performance after disruption events have occurred, using this information to retrain the predictive models. The system improves its ability to predict future disruptions, determine effective disruption mitigation strategies, and minimize the time required for system recovery in the event of future disruptions.

In addition to retraining the models, the layer also supports the supply chain in terms of explainability and governance through the monitoring of model behavior, decision confidence, and system performance. The integration of the learning feedback layer enables the supply chain system to become self-improving, allowing the system to respond to new risk profiles and conditions. This is crucial in ensuring the system's resilience in the face of uncertainties.

4.6 Architectural Implications for Resilience

Collectively, this architecture enables the transition from static resilience approaches to dynamic, intelligence-enabled resilience approaches. This architectural perspective enables the rapid sensing, decision-making, and adaptation that can be provided by the integration of machine learning across data intelligence, risk anticipation, decision execution, and learning feedback. This architectural perspective enables organizations to develop an architecture that is scalable and extensible for the strategic implementation of AI as part of their resilience approach, rather than simply as various analytical tools.

5. Machine Learning Framework for Adaptive Decision-Making

In this section, the machine learning framework will be used to define the adaptive decision-making process within the developed AI-driven resilient supply chain architecture. The architectural layers will define how AI capabilities are incorporated within the supply chain, whereas the framework will define how machine learning processes logically occur, enabling decisions that can detect supply chain disruptions and learn from those decisions. The framework will incorporate predictive, prescriptive, and feedback learning.

5.1 Sense–Predict–Decide–Act–Learn Framework Logic

The proposed framework incorporates a closed sense-predict-decide-act-learn cycle to allow supply chains to dynamically adapt their behavior to evolving risk conditions. In the sense phase, data is collected in real-time and near-real-time from both internal supply chain operations and external supply chain environments. The data streams are used as input for probabilistic inference rather than deterministic rules.

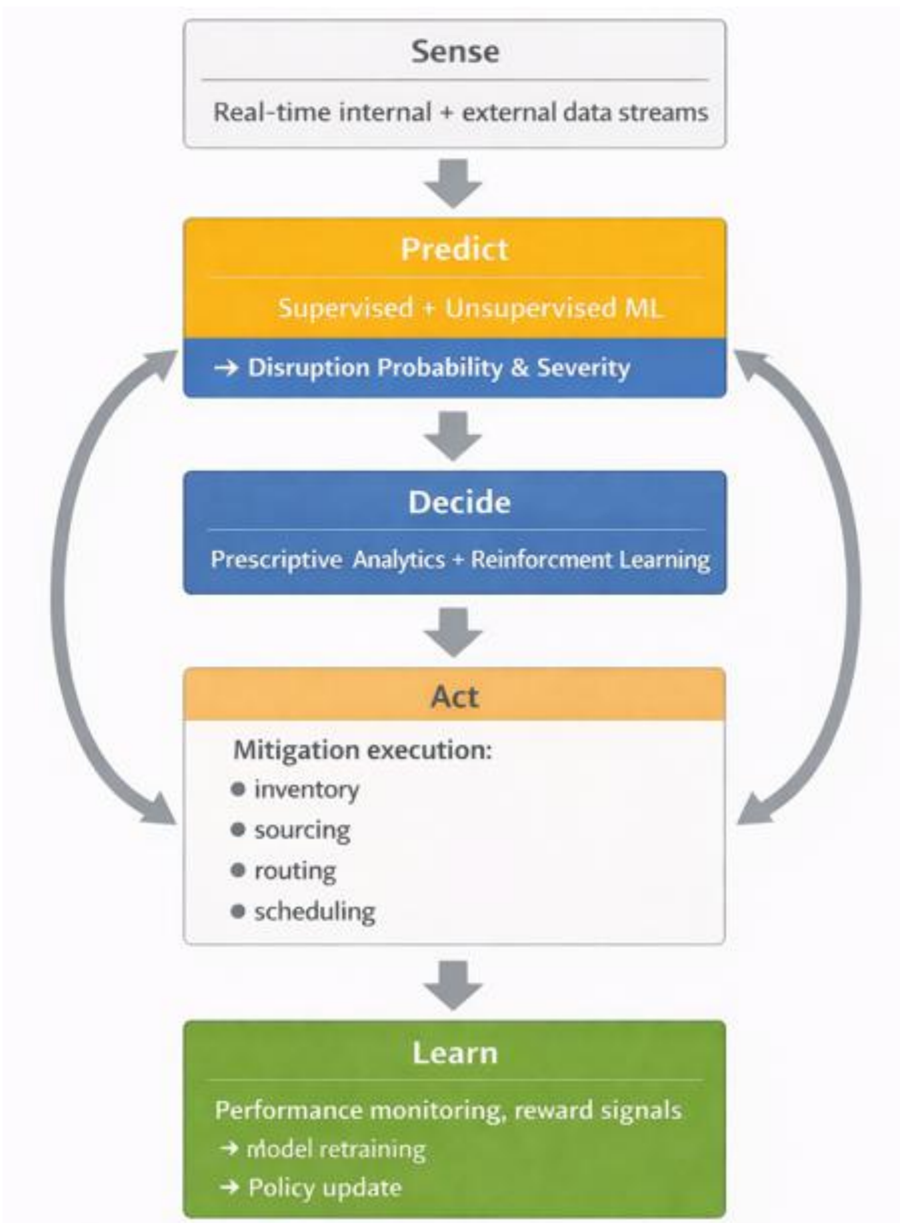

Fig 3. Closed-loop sense–predict–decide–act–learn framework

The figure shows a closed-loop sense, predict, decide, act, and learn approach for adaptive supply chain decision-making. In this approach, internal and external data are sensed in real time and subsequently analyzed using supervised and unsupervised machine learning models to predict potential supply chain disruptions. Prescriptive analytics and reinforcement learning are also used to select a decision, with mitigation strategies implemented in operations and subsequently utilized to learn and improve supply chain resilience.

In the predict phase, supervised and unsupervised learning models are used to produce predictions of disruption likelihood, severity, and propagation. Unlike traditional predictions, these models produce probabilistic risk distributions rather than point estimates. The predictions are used to inform the decision phase, where different mitigation strategies are evaluated.

The decision phase applies prescriptive analytics and reinforcement learning methods to decide response actions that trade off multiple objectives, like cost efficiency, service continuity, and resilience. The actions are executed within the system in the act phase. The system performance with regard to the outcomes is monitored. The learn phase updates parameters, risks, and decisions with regard to outcomes that have been realized, hence allowing for system improvement through a series of disruption events.

5.2 Adaptive Policy Learning under Uncertainty

An important aspect of this framework is that it has the potential to facilitate adaptive policy learning in a situation where there is incomplete information as well as non-stationary dynamics. In this regard, mechanisms of reinforcement learning are leveraged with a purpose to obtain decision policies through interaction with the supply chain system instead of relying on fixed optimization policies. In other words, through observing changes in the system's state as well as reward signals like recovery time, stability of service levels, or mitigation costs, the learning agent refines its action selection policy.

An interesting aspect of this framework is that it has the potential to allow decision agents to exploit their existing effective actions as well as explore alternative actions when faced with unprecedented events. In other words, through leveraging a balance between these two mechanisms, the decision agents are capable of adapting well to familiar situations as well as unprecedented events. In this regard, decision policies converge over time that increase resilience across a range of disruption events.

5.3 From Reactive Response to Adaptive Resilience

The proposed machine learning framework enables a paradigm shift in the decision-making approach of the supply chain, from reactive responses based on set rules to adaptive resilience based on learning. Through a series of disruption cycles, the system is able to internalize learning from experience, increase the accuracy of predictions, and increase the efficacy of mitigation. Resilience, therefore, is a natural attribute of the system rather than a manually engineered one. The proposed machine learning framework, therefore, ensures the tight integration of sensing, predicting, decision-making, and learning, thus enabling the supply chain not only to recover from disruptions but also to become more resilient to future disruptions. The proposed machine learning approach, therefore, creates the conceptual bridge between AI-enabled analytics and resilient supply chain architectures, thus placing machine learning at the center of strategic facilitation of long-term operational sustainability.

6. Evaluation Metrics for AI-Driven Resilience

To assess the concept of resilience within AI-enabled SC systems, it is essential to use metrics that are more advanced than traditional SC system performance metrics such as cost, fill rates, or service levels. These metrics remain important but do not address the system's ability to foresee disruptions or enhance performance over time. Hence, this research proposes a set of metrics for the evaluation of AI-enabled adaptive decision-making architectures for SC systems.

6.1 Recovery and Survival Metrics

The two fundamental resilience measures are time-to-recover (TTR) and time-to-survive (TTS). Time-to-recover is the measure of the time required to recover to acceptable performance levels after the occurrence of a disruption in the supply chain, while time-to-survive is the measure of the time that the supply chain can survive before the performance level is adversely affected. In the case of AI, the improvement in time-to-recover and time-to-survive is a measure of the effectiveness of anticipation and mitigation decisions taken through the help of machine learning models.

6.2 Decision Responsiveness and Adaptation Metrics

The key to AI-enabled resilience is the speed and quality of decision responses to uncertainty. Decision latency is the time between the detection of disruptions and the selection of an action to mitigate the disruptions. It is an important measure of the speed of decision processes. Adaptation speed refers to the rate at which decision policies respond to changes in risk patterns or conditions. Overall, these metrics are important in assessing the ability of the system to go beyond static decision rules and move towards learning.

6.3 Learning and Improvement Metrics

A key characteristic of resilient capabilities facilitated by artificial intelligence is the possibility for continuous learning. Learning efficiency is used to measure the rate at which system performance is improved with each subsequent disruption event. Such improvements in predictive accuracy, mitigation effectiveness, or recovery capabilities are used to measure adaptive intelligence. Such measurements are used to distinguish resilient learning systems from traditional decision support systems, where there are no improvements in system performance with each subsequent disruption event.

6.4 System-Level Resilience Assessment

In order to determine the results of the holistic resilience, the proposed metrics should be evaluated in a collective manner. The benchmarking of scenarios can be conducted in order to compare the AI-driven systems with the traditional rule-based systems in the presence of the same disrupting factors. Such an evaluation provides a framework for the examination of the trade-offs between the efficiency and resilience of the systems, along with the strategic value of the AI systems in the dynamic environment.

7. Managerial and Policy Implications

The proposed AI-enabled architecture for the resilient supply chain has significant managerial and policy-making implications. The reframing of the concept of resilience in terms of adaptability and learning facilitates the transition of organizations/institutions from reactive risk management approaches to more proactive approaches of intelligence-based decision systems.

7.1 Managerial Implications

The findings, therefore, highlight the importance for supply chain leaders to think of AI as a strategic capability for building supply chain resilience, as opposed to an analytic tool. The management should focus on investing in technologies that facilitate an integrated end-to-end approach, as opposed to developing individual AI projects that are often fragmented. The multi-layered structure provides a framework that helps organizations adopt AI incrementally without disrupting existing processes.

The framework also stresses the need for new managerial competencies. This includes the need for cross-functional collaboration among supply chain, data science, and risk management teams, as well as governance structures that enable human-AI collaboration, including the need for managers to set clear escalation points, clear decision ownership, and accountability mechanisms to ensure that AI recommendations align with the organization's risk appetite and objectives. Within this framework, the role of explainable AI is seen as critical for establishing trust in AI decisions, particularly in critical disruption scenarios.

Furthermore, the evaluation metrics used in this research provide the manager with a way of measuring resilience performance beyond efficiency-based measures. By monitoring the efficiency of adaptation, decision latency, and learning efficiency, the long-term value of AI-based resilience can be quantified and justified.

7.2 Policy Implications

From a policy point of view, the proposed system has some implications for various national- and sector-level initiatives that seek to improve supply chain resilience. It may be noted that policymakers might use AI-based architectures to improve early warning systems, protect critical infrastructure, and develop response strategies. Developing standardized data sharing protocols and interoperability systems is vital to support cross-organizational risk anticipation.

The adaptive qualities of AI-driven decision-making present important issues in terms of governance and ethics. There is a need for policymakers to develop rules that promote transparency, accountability, and auditability in AI-driven supply chain decisions, particularly in industries that are sensitive to supply chain disruptions, such as healthcare, energy, and food. Additionally, there is a need for AI literacy and workforce re-skilling as a means of enabling organizations to effectively engage in intelligent resilience systems.

Consequently, these managerial and policy implications of AI-driven supply chain resilience emphasize the need for a coordinated response that combines technological innovation with organizational and regulatory innovation.

8. Limitations and Future Research Directions

Despite the conceptual contributions of the research, there are also limitations associated with the current research that provide directions for future research. Firstly, the proposed architecture for the AI-driven resilient supply chain is developed using the design science research methodology and conceptual modeling, instead of using empirical validation with large-scale operational supply chain data. Although the research methodology is appropriate considering the proprietary nature of disruption data, future research can also attempt to validate the proposed framework using large-scale supply chain data.

Second, the evaluation of the suggested framework is based on scenario-based reasoning, not quantitative simulation or optimization tests. Even though scenario-based validation is highly accepted in resilience research, further research can be conducted to extend the framework using simulation modeling, digital twin environments, or agent-based modeling to quantitatively evaluate the benefits of resilience under different disruption levels.

Third, the existing framework prioritizes adaptive decision-making in architectural terms without specifying certain algorithmic approaches and parameter settings. Future research should consider carrying out comparative studies of different machine learning models, for instance, diverse versions of deep reinforcement learning, combined optimization-learning models, and graph-based models in terms of their efficiency in promoting resilience in supply chains of different tiers.

Future research should extend to more organizational and ethical aspects. Future research could extend to examining how trust, explainability, and governance factors affect human-AI collaboration for critical supply chain decisions. Other areas for future research could include examining data-sharing incentives, cybersecurity concerns, and regulatory factors to improve the generalizability of AI-based supply chain resilience architectures.

The above limitations do not undermine the significance of this research but rather underscore its role as an initial framework to open up many avenues for further research on intelligent, adaptive, and resilient supply chain systems.

9. Conclusion

Supply chains are now facing persistent uncertainty, where disruptions are not exceptional events but rather persistent conditions to be managed. Within this context, traditional risk management and supply chain resilience approaches are ineffective in managing supply chain disruptions. To this end, this paper aims to address these challenges through the development of an artificial intelligence-based resilient supply chain architecture, which seeks to reconceptualize supply chain resilience as an adaptive and learning-based approach.

Following a design science research methodology, the present paper develops a layered architecture for data intelligence, machine learning-based anticipation of risks, decision support, and learning. By establishing a systematic link between supervised, unsupervised, and reinforcement machine learning methods and different classes of supply chain risks, the framework enables the anticipation of disruptions, mitigation of risks, and improvement of the system through learning from experience. The inclusion of the learning component and the collaboration with humans also differentiates the architecture from conventional decision support systems.

In addition to the theoretical contributions, the present study is significant to the advancement of the measurement of resilience by proposing the development of the evaluation metrics, which measure the speed of recovery, the responsiveness of decision-making, and the efficiency of learning, all of which are significant to the assessment of the efficacy of AI-based adaptive systems. Overall, the proposed architecture, the machine learning approach, and the resilience metrics provide a holistic base upon which the development of intelligent supply chains can be achieved.

By developing a framework for conceptualizing artificial intelligence as a strategic enabler for adaptive resilience, as opposed to a set of individualistic analytical tools, this research adds to the ongoing discussion surrounding intelligent operations and supply chain resilience. The framework developed within this research provides a clear direction for how supply chain practitioners and academics can continue toward developing self-learning, anticipatory supply chain strategies that can sustain competitive supply chain performance within an environment of ongoing disruption.

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