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A Hybrid Framework for Retail and Paint Manufacturing

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***Abstract*—Disruptions in supply chains cause severe financial losses, necessitating exploration of Agentic AI solutions for Supply Chain Resilience Management. Agentic AI differs from traditional automation, offering innate problem-solving, adaptive-learning, and collaborative capabilities. Enabling Agentic capabilities in supply chain systems can enhance Resilience Strength by supporting accurate decision-making and expanding the range of explored solutions. Concerns regarding safety, accountability, and over-trust in Agentic systems need to be addressed. A Hybrid Agentic AI-Driven Resilience Engineering Framework comprises a central technology area for Resilience Strength and several application areas for demand and supply networks. Scenarios for Retail and Paint Manufacturing demonstrate expected contributions in terms of inventory cost, stockout level, and service level performance indicators.**

Supply chain disruptions incur significant financial losses. Agentic Artificial Intelligence—AI with intrinsic problem-solving, adaptive-learning, and collaborative abilities—has been highlighted as a possible contributor to Supply Chain Resilience Strength. Concerns over Agentic features such as safety, accountability, and over-trust require exploration. Enabling Agentic capabilities in supply chain systems can improve Resilience Strength by facilitating precise decision-making while broadening the spectrum of potential solutions. Agentic AI departs from conventional automation by providing appropriate support for semi-structured decision environments. Supply Chain Resilience Management based on Agentic AI can leverage these features to preemptively mitigate novice-level disruption risk, fortifying the system's ability to absorb, respond, and recover from a wider array of causes and types of disruption.

Keywords—Agentic Artificial Intelligence, Supply Chain Resilience Management, Hybrid Agentic AI Framework, Resilience Engineering, Adaptive Decision-Making Systems, Autonomous Problem Solving, Collaborative AI Agents, Demand–Supply Network Optimization, Disruption Risk Mitigation, Inventory Cost Optimization, Stockout Reduction, Service Level Optimization, Semi-Structured Decision Support, AI Safety and Accountability, Human–Agent Collaboration, Resilience Strength Metrics, Intelligent Supply Chain Systems, Proactive Disruption Management, Multi-Agent Orchestration.

I. INTRODUCTION (*HEADING 1*)

The increasing volatility of global markets imposes new challenges to supply chain management (SCM), especially in terms of resilience, which is defined as the capability of a supply chain to bounce back from disruptive events. Recent floods and droughts have highlighted the importance of understanding the links between natural and economic ecosystems for demand- and supply-side equilibrium restoration. In response to increasing uncertainty arising from COVID-19 pandemic waves, transportation costs, and consumer behavior changes, companies are increasingly considering supply chain network design as a demand-forecasting-and-inventory problem. The introduction of an agentic artificial intelligence (AI) approach, combining elements of data-driven-machine-learning and agent-based decision support, provides a vital new perspective for enhancing resilience.

The objectives are to define the concept of agentic intelligence in the context of SCM, propose a design for a hybrid AI implementation of supply chain resilience, and apply it to the fields of retailing and paint manufacturing. The former involves forecast-driven inventory management, exploitation of demand-and-supply-side correlations, and predictive-analytic testing of how much improvement can be gained through demand-influencing actions. The latter combines SCM risk-sharing analysis with retail-optimal-network demand controlling.

A. Overview of the Study

The present work contributes to supply chain resilience by exploring how agentic artificial intelligence can reduce cocoa retail–chocolate manufacturing supply network disruptions; thus, the study examines how agentic AI reacts, interacts, and communicates with network stakeholders. Agentic intelligence differs from current AI-enabled supply chain automation, which reduces routine activities but remains deterministic and requires extensive human intervention when faced with sudden disruptions. Agentic systems exhibit human-like functional capabilities—autonomy, adaptation, learning, collaboration, communication, perception—to handle novel supply chain situations. A hybrid architecture based on agentic features offers a complementary approach to the other automated management layers (control, management, maintenance) and the computationally-intensive modelling and simulation. Diversity in architecture reduces impact when part of the framework is disabled or severely degraded. Agentic intelligence drives two complementary cross-layer support functions: (1) optimising demand forecasting and inventory replenishment of fruits-and-vegetables suppliers; and (2) designing the supply network and supporting supplier collaboration.

A demand forecasting and inventory optimisation approach, integrating deep-Gaussian-process-based modelling and reinforcement learning, enables suppliers to anticipate future needs of cocoa-chocolate production. Performance is evaluated with demand data from a Swiss wholesaler and fruit-market price lists; low error levels across supermarket categories indicate the approach's robustness. An agentic articulation allows supermarkets to optimise orders, thus improving inventory levels. Under- and over-stocking alerts support suppliers during shortages, while a model-based decision-support system enhances the chances of stock-out avoidance. These features are relevant to action-baking-supply stores; impact-modelling-decreasing customers, pandemics, and natural catastrophes provide additional insight.

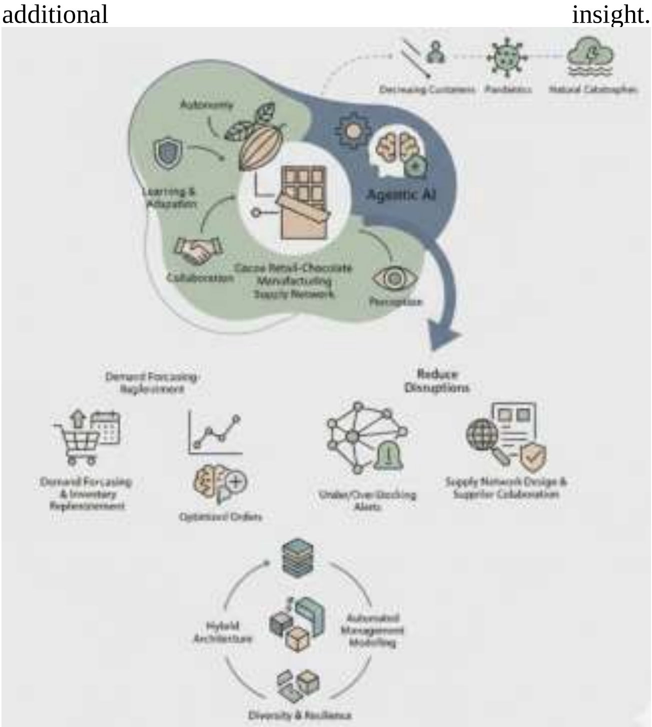
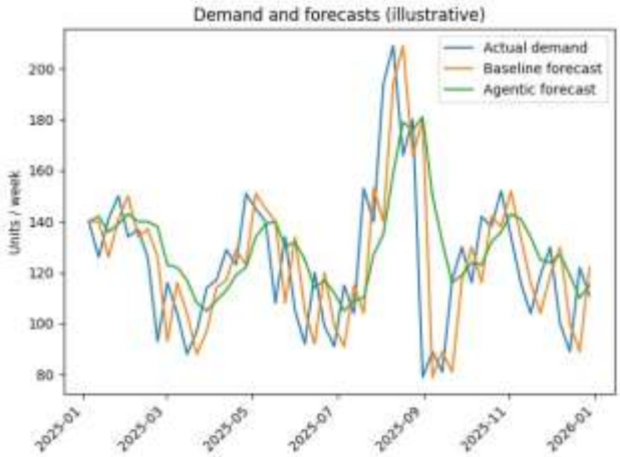


Fig 1: Agentic AI for Supply Chain Resilience: A Hybrid Architecture for Autonomous Disruption Management and Multi-Stakeholder Collaboration in Cocoa-Chocolate Networks

II. THEORETICAL FOUNDATIONS

Supply chains are increasingly regarded as risk-prone ecosystems. Supply chain resilience is the key construct to ensure timely and efficient recovery from adverse events. The concept of a resilient supply chain that improves supply chain robustness, redundancy, and adaptability and thus moves the supply chain closer to being risk-free is often proposed. Promising approaches supporting supply chain resilience include hybrid AI frameworks. Hybrid frameworks consist of cooperating and interacting components with orthogonal competencies and are designed either to assist human decision-making or to fully control decision tasks.

Agentic AI approaches are introduced as a particular subset of hybrid intelligence, whereby human-AI cooperation occurs through advanced forms of dialogue. Human agents delegate decision tasks to AI agents that can solve the tasks more efficiently and effectively than humans. AI agents propose decisions to their human counterparts only in situations where they anticipate that the respective human agent is more competent for the decision task than the AI agent. All learning and adaptations are induced by human agents, with the AI agents revealing their learning conclusions only upon explicit request. Contrary to the existing literature on hybrid intelligence, the agentic AI approach places an emphasis on agent autonomy and AI decision-task ownership.



Equation 1) Demand forecasting model: ARIMA(p,d,q)

Step 1 — Differencing to achieve stationarity

ARIMA has differencing order d. Define the differenced series:

$$Y_t = \nabla^d D_t$$

For example:

- if $d = 1$: $Y_t = D_t - D_{t-1}$
- if $d = 2$: $Y_t = (D_t - D_{t-1}) - (D_{t-1} - D_{t-2})$

Step 2 — ARMA(p,q) on the differenced series

Model Y_t as:

$$Y_t = c + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} \; + \; \varepsilon_t \; + \; \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

where:

- c is a constant,
- ϕ_i are AR coefficients,
- θ_j are MA coefficients,
- ε_t are residuals (forecast errors).

Step 3 — Compact operator form (optional but standard)

Using lag operator L where $LY_t = Y_{t-1}$:

- AR polynomial: $\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p$
- MA polynomial: $\theta(L) = 1 + \theta_1 L + \cdots + \theta_q L^q$

Then:

$$\phi(L)Y_t = c + \theta(L)\varepsilon_t$$

and since $Y_t = \nabla^d D_t$:

$$\phi(L)\nabla^d D_t = c + \theta(L)\varepsilon_t$$

Step 4 — Forecast (mean prediction)

The one-step-ahead forecast is the conditional expectation:

$$\widehat{D}_{t+1|t} = \mathbb{E}[D_{t+1} \mid \mathcal{F}_t]$$

A. Agentic Intelligence in Supply Chain Contexts

Agentic intelligence constitutes a growing field within artificial intelligence research. A broad definition refers to computer systems that act in an environment using perceptions through sensors and performing actions using actuators, with a perception—decision—action cycle reminiscent of living systems. A narrower definition refers to systems endowed with at least some of the properties of living systems, such as the ability to adapt to changes in their environment, collaborate with others, and learn from experience, with a structure resembling that of agent-based systems. A further, even narrower, definition targets systems that are self-contained and self-governing—geared toward their own survival and continuously learning and improving their operations—like biological organisms, the AI definition incorporates only autonomously operating systems, without the self-governing requirement.

A fundamental distinction separates agentically intelligent systems from those that are merely automated. Automation typically targets repetitive tasks characterized by a well-defined and structured environment. Agentically intelligent systems, by contrast, traverse a considerably wider range of tasks, enabling performance in environments requiring adaptation and learning; also, agentically intelligent systems do not need to operate at full autonomy. Hence, some may be executed under human supervision, incorporating an aspect of human cooperation without full automation; others serve merely as decision-support tools to assist human actors in their decision-making. In a supply chain context, agentic AI possesses three core capabilities—autonomy, collaboration, and learning—each with its own detailed features.

B. Hybrid Frameworks for Resilience

Agentic intelligence, capable of supplying preparedness, is a widely sought capability for all aspects of life, now including supply chains. Agentic supply-chain systems use hybrid frameworks to inject hybrid forms of intelligence into components of conventional supply chains, thus enabling those components to respond to their environment and plan local actions in pursuit of goals aligned with those of the organisation itself. The foundational aspect that underpins the demand for agentic supply-chain systems is their ability to provide resilience. Resilience is critical in these times, when supply chains, acting in a market largely devoid of concern for long-term relationships, are being driven by cost-efficiency metrics alone, making them fragile and ready to buckle under distress. Agentically-enhanced supply chains, created using a hybrid framework, provide the widely sought capability of preparedness for coping with the unexpected.

The literature on hybrid frameworks for resilience has presented a rich range of solutions. While the concepts presented in such solutions are important, they need to be united into a coherent, formal structure that clearly articulates their unique contributions to supply-chain resilience. A system architecture that provides integration by delineating a layer for data and another for the tasks of perception, decision, action, agents, and their respective routing mechanics is now elaborated.

III. METHODOLOGICAL APPROACH

The new hybrid architectural framework supports AI agents acting alone or supported by collaborative decision-making and autonomous optimization capabilities. An overview is presented, detailing its data architecture and the models and algorithms controlled by agentic agents.

Supporting the proposed architecture is an integrated system designed to enhance the resilience of supply chains in the retail sector and related industries such as paint manufacturing. Data from third parties, organizations like the OSC and YEEER, and literature provides the foundation for agents' operations. These exploit large volumes of historical data to conduct predictive analytics, optimize decision-making under uncertainty, and share computations among peers within the same area of domain expertise. Targeted enhancements also improve multimodal data integration, providing a richer context for decision-making. Any organization can operate agents without major investments in computational infrastructure or staff expertise.

The data layer underpins all decision-making modules and functions as a service-based architecture to enhance network-wide data quality and share filtered, standardized information. AI agents consider their specific area of domain expertise and rely on dedicated, de-facto standard sets of ontologies and protocols (e.g., OGC, ISO 19100 series) that manage the internal complexity of effective implementations. Domain ontologies (e.g., GAIA, OSC, FMI) serve as a basis for multimodal integration and interoperability, supporting the activities of data-hungry DACG-F models defined in the supply network design and SMPI subdomains.

System	Holding cost	Stockout cost	Order cost
Baseline (naive forecast)	4,293	128	990
Agentic (improved forecast)	4,156	128	990

A. System Architecture and Data Integration

An agentic AI hybrid framework delivering resilience-enhancing predictive and prescriptive e-ntelligence capabilities comprises five layers: perception, action, decision, data, and policy. The system architecture supports a combination of learning and automated decision-making, facilitates mutual assistance and outsourcing of tasks among intelligent agents, and allows for integration with existing enterprise resource planning and supply chain management systems. Integrated action and cognition are enabled by a combination of digital and intelligent agents, each tailored to specific tasks. Realization relies on sound data integration. A resilient supply chain requires virtual connections with the stakeholders' supply networks. Digital agents serve at one end by collecting, transforming, and packaging relevant information. Intelligent agents probe the supply networks and respond to their requests. Accordingly, the presentation of the data layer emphasizes data formulation, quality, and integration should meet at least one of the four underlying conditions established by Wang et al. for a successful data update and sharing: Same value, same meaning, same format, or same origin.

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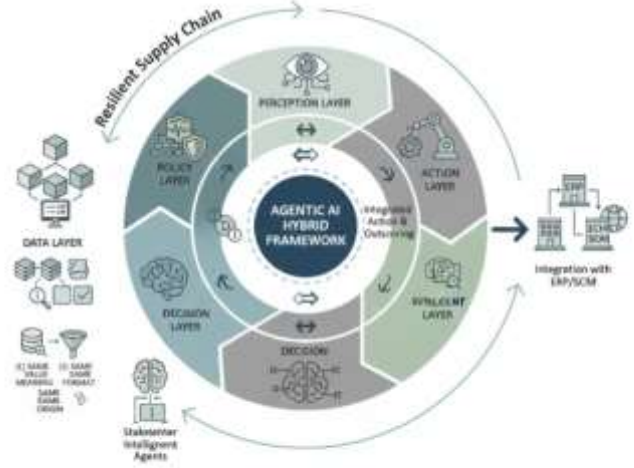


Fig 2: Agentic Polycentricity: A Five-Layer Hybrid AI Architecture for Resilient Supply Chain Predictive and Prescriptive Intelligence

B. Decision-Making Models and Algorithms

Optimally achieving supply chain goals by solving a multitude of complex problems involves rigorous and systematic processes of decision-making. In agentic AI-enabled hybrid frameworks, these processes encompass modeling, optimization, predictive analytics, and machine learning algorithmic capabilities embedded in the underlying system architecture. Deep learning-based models for demand forecasting and neural network-based algorithms for inventory optimization are developed for retail applications. Scenario analyses evaluate expected improvements. Layering is employed to delineate decision-making capabilities in the context of supply network design and supplier collaboration. Supply network design addresses network rationalization, supplier risk-sharing, and network agility.

Decision-making model and algorithm specification is vital for an effective supply chain architecture. Multi-fidelity approaches combine analytical models with simulations to enable different modelling fidelities, depending on data description and availability, and the associated computational burden that can be tolerated, thus supporting risk and complexity scaling with supply chain size. Demand forecasting and network design for heterogeneous products are complex problems that often defy inference across scales requiring simulation. Other problems, such as inventory optimization and supplier selection, can benefit from explicit analytical representation. Decision-making capabilities are implemented as libraries of models and algorithms, accessible via standardised application programming interfaces with explicit descriptions of input and output requirements.

IV. AGENTIC FEATURES AND CAPABILITIES

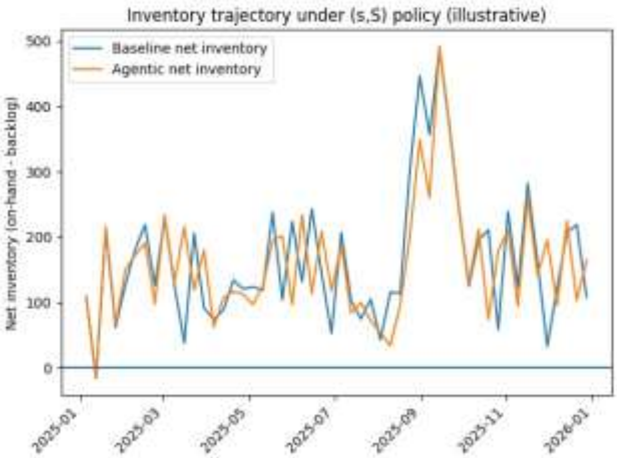
Autonomy, adaptation, and learning are prominent characteristics of the proposed framework's agentic features. The agentic systems are, in principle, entirely autonomous but operate under defined rules/boundaries. These boundaries constrain the range of actions available to the agents. The decision-making models for the agents are designed with safety consideration (hence enable decision-making only within risk-free boundaries; only if all the key demand-, supply-, and risk-related input information falls within acceptable levels). Formalized accountability protocols define the mechanism for assigning and tracking accountability for the decisions made and subsequent actions taken.

Collaboration and human interactions are central components of the framework. Supporting structures and processes are defined to strengthen and accelerate these interactions. Several collaborative interfaces are defined to facilitate human interaction with the agentic systems when required; they include two adjoining systems, namely, a human-team trust-building framework for collaborative decision-making and an agentic escalation mechanism. The trust-building framework embeds an artificial neural network model for supporting collaborative decisions and services as a dynamic support structure for trust building/acting in a two-way interaction with the users/end consumers.

A. Autonomy, Adaptation, and Learning

Autonomy, adaptation, and learning are key features of agentic systems. Autonomy reflects the capacity to perform tasks with some degree of independence, without requiring continuous intervention by other agents. Autonomy is characterized in terms of different levels, from fully autonomous systems that operate independently of human and other agents to systems that require human supervision or approval for a subset of their decisions. In this context, adaptation refers to the ability of the system to adjust to variations in the environment or in system performance, including forecast errors that deviate from a known range. Learning specifically indicates the capacity to detect such changes and to define appropriate corrective actions.

CRISP-DM processes exhibit a high level of autonomy, encompassing data management (facilitating production of quality data and models that optimally serve the supply chain decision systems), infrastructure (its working is managed by predefined service-level agreements, action plans, and budgets), and machine learning (adaptation). However, this adaptation capability may need to be constrained during simulation phase or during trustworthy establishment, allowing adaptation only when certain conditions are met. Safety concerns related to the predictive algorithm are actively monitored by the supervision loop of the human–AI interaction design. Level-1 adapted learning is implemented via preventive countermeasures and risk-sharing agreements among suppliers; learning capability is implemented at the decision level, where risk assessments (e.g., risk forecast-based network consolidation) are frequently computed and monitored.



Equation 2) Volatility model: GARCH(r,s) on ARIMA residuals

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim \text{i.i.d. } (0,1)$$

Step 1 — Conditional variance equation

A GARCH(r,s) model:

$$\sigma_t^2 = \omega + \sum_{i=1}^{r} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \, \sigma_{t-j}^2$$

where:

- $\omega > 0$,
- $\alpha_i \geq 0, \beta_j \geq 0$,
- typically $\sum \alpha_i + \sum \beta_j < 1$ for stability (common assumption).

Step 2 — What "combined ARIMA–GARCH" means

- **ARIMA** gives the conditional mean $\widehat{D}_{t+h|t}$
- **GARCH** gives the conditional uncertainty $\hat{\sigma}_{t+h|t}^2$

So demand forecast can be treated as a distribution:

$$D_{t+h} \mid \mathcal{F}_t \approx \mathcal{N}\left(\widehat{D}_{t+h|t},\ \hat{\sigma}_{t+h|t}^2\right)$$

B. Collaboration and Human–AI Interaction

Robust and truly agentic supply chain systems gather and react to information in an autonomous and internalized manner. However, such full autonomy needs to be an escalation path. A critical fraction of the information coming from the physical world is constantly filtered and fed to the perception layer of the hybrid framework, while the logic of the decision layer has been designed to accept business expert or experienced human input that can extend or enrich synthetic knowledge sources. This provides substantial backing for rapidly addressing situations that would require less time to interpret or understand by a human than by an AI. Such human-in-the-loop facilitation is important to apply into critical situation being the alternation of a predicted first-order tornado hitting an area or the disruption of a logistic corridor of suppliers due a pandemic situation or war activity.

Trust plays a fundamental role. The limits to human–AI interaction are evaluated when a real-life example with external data of a machine-level conversational AI ad-hoc pad has been applied to the scaled supply chain framework using pencils production. Human input is question-guided, avoiding any expansive elaboration. For smooth dialog, the UI initiates the conversation as being the one on control of the pace, though it is actually a predefined process. Once first-order usefulness and robustness are demonstrated, the entire layer for conversation with new integrated components can be left to the AI to manage, requiring specialized trust dialogue about delicate and important information with predictions being highly innovative and no relevant salaries having previous data.

V. APPLICATION DOMAIN: RETAIL AND PAINT MANUFACTURING

The agentic AI-driven supply chain resilience framework is applied to two complementary domains: retail and paint manufacturing, with different emphases. The retail dimension focuses on demand prediction and the consequent inventory optimisation problem, while the paint manufacturing view concerns supply network design decisions—from rationalising the supply network to enabling dynamic risk-sharing collaborations with suppliers.

Demand prediction and inventory optimisation models are presented first. Demand for a selected group of products is predicted by a combined ARIMA-GARCH model, the outputs of which are used with stock-level thresholds in a stockout-cost-based control mechanism. The effect of using demand estimations obtained from the hybrid predictive model for stock replenishment control is compared to the performance of these controllable inventory levels using the raw historical demand data. The evaluation is conducted through wholesaler-case-scenerio-testing concerning stockout events, total stockholding cost, and demand) supply chain management cost. The second-class performance measure relates to the application of the hybrid predictive model within a preventive-stock replenishment-controlling process. Here stockouts are not quantified but the focus is on preventiveness, namely, stocklevels being maintained just above the stockout threshold or on the contrary, being overdue.

A. Demand Forecasting and Inventory Optimization

Demand forecasting and inventory optimization represent critical supply chain decision-making problems that are closely interrelated. Forecasts are the primary drivers of supply chain management decisions, since a forecast at one node lays the foundation for manufacturers, suppliers, transportation providers, and retailers to react, respond, and employ measures to ensure optimum fulfilment of customer demand with little or no stockouts. Therefore, accurate forecasts can help all supply chain participants achieve better customer service levels at minimal inventory investment. Agency theory along with predictive analytics and optimization models are applied to address these problems, leveraging historical demand patterns, networked demand data, and trend and seasonality components as data inputs. The performance of demand forecasting and inventory optimization is evaluated through five scenarios using a multiple classification method and real-world consumption data.

Modeling capacity and production, suppliers choose their technology and production capacity levels in the early stages of game play, without full knowledge of the strategic demand-shifts that will be encountered later. Then, downstream suppliers make their production choices, knowing the other suppliers' technology strategies but uncertain about capacity levels. During the last stage, market demand for the downstream supplier's products is revealed, and only then does the downstream supplier make its production choice. The lack of full coordination among the players introduces inefficiencies in the system, which are evaluated based on equilibrium prices and profits. Prescriptive analytics provide solutions and recommendations that can be adopted by suppliers to better cope with the impact of demand uncertainty on demand-supply cooperation. Performance is assessed in terms of supply network rationalization, risk-sharing agreements, and supplier agility.

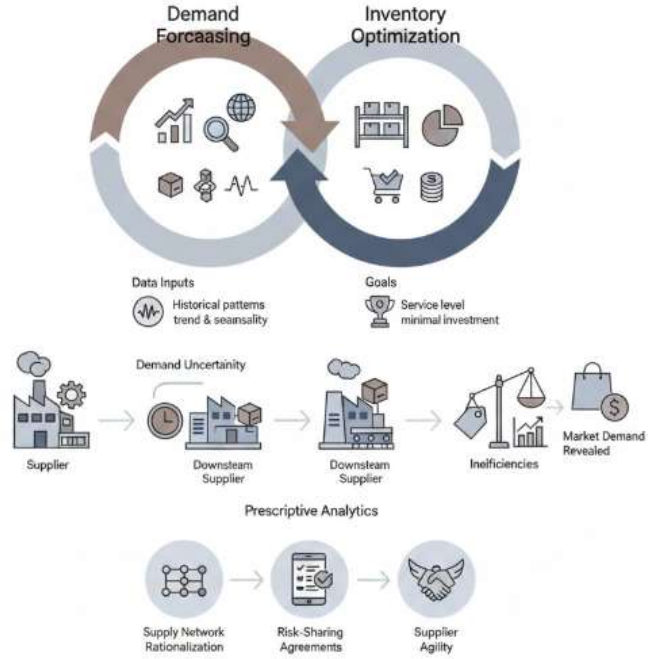


Fig 3: Integrated Demand Forecasting and Inventory Optimization: A Prescriptive Analytics Framework for Mitigating Strategic Information Asymmetry and Supply Chain Inefficiency

B. Supply Network Design and Supplier Collaboration

Robust supply network design is key for minimizing long-term cost while mitigating the impact of disruptions on delivery performance. Capturing the interdependencies of decisions taken at the respective suppliers and manufacturers of supply network partners helps to rationalize the makeup of supplier pools. Furthermore, risk-sharing collaborations that take the cost and delivery risk of multiple deliveries across the pools into account support resilience. Finally, continuously monitoring variability in demand, supplier capabilities, and cost ensures that the requirement can always be fulfilled at the lowest possible total cost at a given level of risk.

Redundancy in supply networks must balance the cost incurred by the equity tied up in, and the risk of nonfulfilment due to delivery uncertainty at, alternative suppliers with the possible penalty cost incurred should the preferred supplier not be able to fulfil the requirement. Network rationalization explores the balance of these two factors in a risk-neutral setting, assessing the potential cost savings from consolidation against the potential penalty cost savings from adding delivery redundancy. Agility requirements must be shared with suppliers if these are to be trusted with additional deliveries that might not be required, and the design of the overall network must enable such risk sharing.

VI. HYBRID FRAMEWORK DESIGN

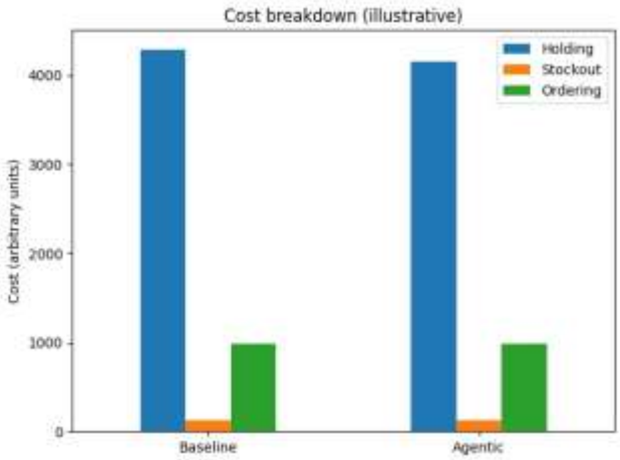
An overview of the hybrid framework architecture is presented, indicating layers and their functions and delineating agent roles. The integration of agentic features with traditional enterprise resource planning and supply chain management systems is described, illustrating how agentic capabilities enhance, but do not replace, existing functionalities. Agent-based frameworks for resilience in supply chain management are reviewed; differences in architecture, data interoperability, and distinction between decision-support and decision-making boundaries are analysed.

The architecture is organized in layers—perception, decision, action—and its design ensures that the agent's capabilities, although novel, enrich rather than supplant existing enterprise resource planning or supply chain management systems. Agentic features are embedded within the data layer to expedite implementation and reduce implementation costs. Supply chain data, including orders, sales, stock levels, forecasts, lead times, supplier performance, and capacities, should adhere to data quality and completeness standards to guarantee reliable results. A supply chain ontology explicitly defines and relates these concepts to facilitate interoperability. Enterprise resource planning and supply chain management data stored in different formats can be integrated using a mediation approach based on standard interoperability schemas.

A. Architecture Overview

The hybrid framework comprises three interacting layers: external perception, internal decision-making based on a digital twin, and action in the external environment. An agent at each layer specializes in integrating and passing information to the layers above and below. Information flowing from bottom to top and outside to inside empowers decision-making algorithms. Information flowing top-down gives the external sensory agents a more comprehensive view of their environments. The decision-support agents utilize all the information at their disposal to recommend actions to group members and corresponding human operators. Information flowing from inside to outside enables digital-twin-based business models that drive a wider range of operational decisions than those made solely based on external perceptions. Classification of the respective agent roles into those that can leverage agent-based decision-making algorithms and those that support human operators' decisions without driving their behavior characterize a hybrid architecture not commonly seen in other agent-based research. The framework can be tuned toward either supporting autonomous decision-making in a specific domain of the business or decision support across multiple domains.

Finally, the architecture enables damage-control decision support, helping businesses with different data ownership structures respond to crises. The detection and adaptive response of an agent's operating area are automated, enabling business network partners without a complete goods-traffic picture to develop predictive demand models for the damage-control phase and take suitable actions. Although the framework can be built on an agent-based architecture, it is sufficiently independent of that implementation choice to facilitate integration with existing enterprise resource planning or supply chain management systems without substantial structural changes.



Equation 3) Inventory dynamics + stockout-cost-based control

Define:

- I_t: on-hand inventory right after receiving replenishments (start of period t)
- Q_t: order quantity placed at end of period t
- L: lead time (periods)
- D_t: demand in period t
- B_t: backorders (unmet demand carried), if allowed

Step 1 — Inventory balance (with backorders)

End-of-period inventory (net of demand):

$$I_{t+1} = I_t + R_{t+1} - D_{t+1}$$

where R_{t+1} is the receipt arriving at $t+1$. With fixed lead time L:

$$R_{t+1} = Q_{t+1-L}$$

If stockouts create backorders, it's cleaner to use **net inventory**:

$$NI_t = \text{OnHand}_t - B_t$$

Step 2 — Reorder point based on forecast over lead time

Forecast lead-time demand:

$$\mu_L = \sum_{k=1}^{L} \widehat{D}_{t+k|t}$$

If we approximate lead-time demand variance using GARCH:

$$\sigma_L^2 \approx \sum_{k=1}^{L} \hat{\sigma}_{t+k|t}^2 \quad \left(\text{or } \sigma_L \approx \sqrt{L}\,\hat{\sigma}_{t+1|t} \text{ as a simplification}\right)$$

Step 3 — Service-level / threshold rule → safety stock

For a target cycle service level α, choose:

$$SS = z_\alpha \sigma_L \text{ Reorder point } s = \mu_L + SS$$

where z_α is the standard normal quantile (e.g., $z_{0.95} \approx 1.65$).

Step 4 — Stockout-cost-based rule (newsvendor form)

If the mechanism explicitly trades holding vs stockout penalty, define:

- holding cost per unit: h
- stockout penalty per unit short: p

Critical fractile condition (one-period newsvendor logic):

$$\mathbb{P}(D \leq s) = \frac{p}{p+h}$$

So:

$$s = F_D^{-1}\left(\frac{p}{p+h}\right)$$

If $D \sim \mathcal{N}(\mu_L, \sigma_L^2)$, then:

$$s = \mu_L + z_{\frac{p}{p+h}} \sigma_L$$

This is exactly "stockout-cost-based thresholding".

Step 5 — Order-up-to (s,S) control (common with forecasts)

A standard policy:

- if inventory position $IP_t \leq s$, order up to S.

Inventory position:

$$IP_t = \text{OnHand}_t + \text{OnOrder}_t - B_t$$

Order quantity:

$$Q_t = \max(0,\ S - IP_t)$$

B. Data Layer and Interoperability

A standardized data schema and corresponding data quality requirements are essential to ensure that these demand-forecasting and inventory-optimization models can be endorsed by the agentic AI solution. The necessary demand–inventory data and models are defined to facilitate a structured evaluation of the models. The data-tested models are expected to deliver superior performance when compared with industry-standard benchmarks. The expectation is that the resultant models will provide a higher level of accuracy than the commonly used single forecasts, for both level and forecast-error measures of performance. Such analysis typically involves modelling the time series of the demand–inventory time series data and back-testing targeted forecasting periods against out-of-sample forecasts from the model.

Demand scenario analyses will be applied to the models aimed at testing their ability to identify subsequent inventory risks. Changes in inbound and outbound supplier lead times, demand and forecasting error, failure, and abort risks, will be considered. The risk stamina of suppliers relative to their position in the supply chain will then be a primary consideration, noting that longer- and shorter-lead-time products may require a different risk-sharing approach. Supply Chain Agility will be a key consideration when optimising the Supply Chain Network design by minimising cost and maximising service level delivery at the lowest possible stock level. Greater anticipation of demand-scenario variability can be achieved by an outsourced component strategy, within a risk-sharing framework, thereby integrating the core and surplus capabilities of both suppliers and manufacturer across all key components and systems.

VII. CONCLUSION

The proposed contributions advance the design of a hybrid agentic intelligence architecture for supply chain resilience. Demand forecasting and inventory optimization models support retail resilience, whereas supply network design and risk-sharing with suppliers enhance resilience in paint manufacturing. The integration of agentic intelligence capabilities into the design extends work on hybrid frameworks. Three agentic intelligence dimensions—autonomy, collaboration, and learning—are characterized and examined.

Unlike conventional automation, agentic intelligence embodies intelligence-driven automation—the capacity of an intelligent agent to engage autonomously in partly automated or decision-support partnerships. Intelligence-driven automation bridges decision-support and autonomous intelligence. In a hybrid architecture, agentically intelligent components operate in partnership with automated components such as an evolving dialectrome or predictive analytics backlog. Intelligence-driven automation promote decision-making and increases supply chain resilience while incorporating explicit safeguards and an appropriate control framework.

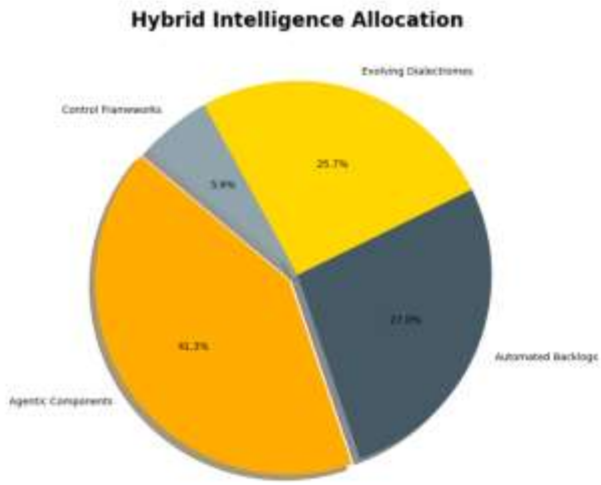


Fig 4: Hybrid Intelligence Allocation

A. Final Insights and Future Directions

Beyond the physical-systems perspective, an agentic AI approach to supply chain resilience encompasses AI-enabled data interoperability, decision support, and AI automation. A hybrid framework accommodates a broader set of agentic features and capabilities while including both higher and lower levels of autonomy in a single architecture. The demand forecasting, inventory optimization, supply network design, and collaborative supplier selection applications in retail and paint manufacturing illustrate these points.

For retail inventory management, demand is forecast using data from multiple sources, including social media, and both the supervised and unsupervised learning algorithms within a Random Forest ensemble predict SKU inventory levels at the weekly level. Adapted inventory control policies optimize inventory levels across replenishment lead times. Scenario-based analyses based on forecast-error metrics assess recommended policies against actual inventory and vendor performance. Overall, the focus is on loss avoidance in a high-service-delivery-environment, low-margin retail setting.

Attention then shifts to supply network design and supplier collaboration for the paint manufacturing industry, where time-sensitive, high-volume, and low-margin products are supplied from vendor networks. A geo-spatial lexicon provides the basis for a novel KPI framework that rationalizes the location of supply points within the network. Subsequently, suppliers are considered as active partners rather than mere sources of raw material supply. Risk-sharing contracts are designed, and the resulting risk-sharing practices, together with vendor capabilities towards agility, are investigated through a combined probability business impact model framework that supports management decision making.

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