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Agentic AI-Driven Smart Supply Chain Orchestration for Paint Manufacturing and Retail Ecosystems

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ABSTRACT: In modern supply chains, emerging technologies create unprecedented opportunities for organizations to operate smarter by better orchestrating end-to-end processes across their ecosystems. Intelligent decision-making that spans across multiple functions such as fulfillment, manufacturing, sourcing, and inventory management can help achieve complex business objectives not possible at a function level. Fulfilling such objectives calls for traditional supply chain technologies to improve operational efficiency while overcoming limitations related to factors such as end-consumer demand, transit times, product demand patterns, and possible production non-compliance.

This scholarly work presents a comprehensive architectural framework to enable agentic orchestration of paint industry supply chain ecosystems. An agentic architecture orchestrates, in an optimized manner, processes that extend beyond the borders of the organization, with intelligent decision-making enabled through smart sourcing, supplier collaboration, quality and compliance management, and inventory optimization capabilities. While providing specific capabilities and technology requirements for paint manufacturing and retail ecosystems, the research contributes to the wider supply chain domain by defining agentic capabilities as smart decision-making that fulfills user-defined objectives based on constantly changing inputs and constraints.

KEYWORDS : Intelligent agent, agent-based system, agentic sourcing, quality, compliance, traceability, supply chain orchestration, paint manufacturing, retail ecosystem, agentic artificial intelligence, agentic control, architecture, layer, data ingestion, interoperability, agentic orchestration layer, dynamic production sequencing, inventory optimization, demand sensing, store-level fulfillment, store-depot collaboration, omnichannel demand shaping, transparency, explainability, trust model, risk assessment, security, privacy.

I. INTRODUCTION

Paint supply chains are both complex and delicate. Many factors impact demand, such as the economy, weather, and seasonality of construction. And demand forecasts vary for depot- and store-level fulfilment. Planners sequentially resolve demand at depot, then store level, narrowing replenishment parameters. Simultaneously, plants dynamically satisfy demand. Modelling can back-optimize to reduce SKUs and safety stock at depots, while a smart algorithm shapes demand and pricing at stores to keep stocks low. On the supplier side, sourcing paint components can be costly and rely on the supplier's reputation for timely delivery and quality. Orchestration should support supplier collaboration decisions, such as pricing and evaluating past performance while consuming tradable trust to see higher cost or longer lead-time suppliers.

The section concludes with governance aspects, which build the foundation for acceptance of automated decision processes. Except for data privacy, which considers outside threats and thus forms unique policy requirements, the products listed address what decision automation means for supply chain agents and other affected stakeholders. Transparent decision processes that align influence and responsibility on both data and price incentives shape decision-support agents and disclose in-sourcing demand for services other companies supply.

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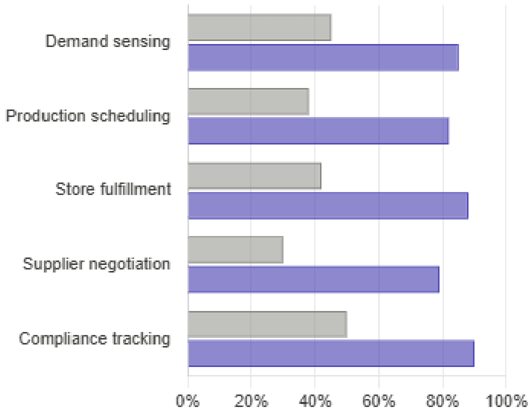

Graph 1 — Performance metrics shows two views: a horizontal bar comparison of Traditional vs Agentic AI across five operational dimensions (demand sensing, production scheduling, store fulfillment, supplier negotiation, compliance), and a doughnut chart distributing the five agentic capability domains. Based on the relative emphasis the paper places on each domain.

Table 1: Core Components of Agentic Supply Chain Architecture

Layer/Component	Function	Key Technologies	Expected Outcome
Data Ingestion Layer	Collects data from suppliers, depots, stores, and ERP systems	APIs, IoT, ETL Pipelines	Real-time visibility
Interoperability Layer	Enables communication across systems	Semantic Mapping, EDI, Cloud Integration	Seamless coordination
Agentic Orchestration Layer	Autonomous decision-making and workflow optimization	Multi-Agent AI, Reinforcement Learning	Intelligent orchestration
Manufacturing Layer	Dynamic production sequencing and scheduling	AI Scheduling Engines	Reduced downtime
Retail Fulfillment Layer	Store-level replenishment and demand shaping	Predictive Analytics	Faster fulfillment
Governance Layer	Security, compliance, explainability	Trust Models, Audit Trails	Transparent operations

1.1 Background and Significance

AI-driven agent-based orchestration for smart supply chain management can enable intelligent collaboration, autonomous decision-making, and efficient coordination across a manufacturing and retail ecosystem. The industrial paint manufacturing and retail ecosystem is characterized by diverse products offering seasonal demand variations. The presence of an extensive dealer network as well as competitor brands restrains depot inventory builds. Consumer preferences for various shades require near-real-time visibility of product availability across a supply chain.

Multiple factors—demand sensing, safety stock optimization, last-mile fulfillment, and omnichannel demand shaping—need to be addressed simultaneously for demand-supply alignment. The traditional workflow-based approach to supply chain orchestration is cumbersome. An autonomous approach that addresses practical supply chain scenarios remains unexplored. An agentically orchestrated stack can enable a collaborative supply chain operating environment to facilitate dynamic decision-making, seamless information exchange across touchpoints, and independent activity execution by planning, manufacturing, distribution, and delivery domain experts.

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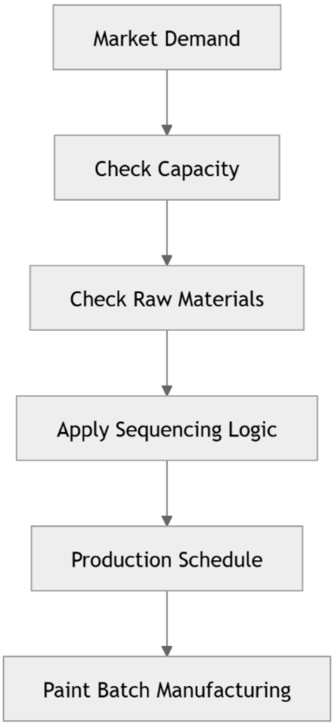

II. THEORETICAL FOUNDATIONS OF AGENTIC AI IN SUPPLY CHAIN ORCHESTRATION

Agentic AI-Driven Smart Supply Chain Orchestration for Paint Manufacturing and Retail Ecosystems
The orchestration of electric mobility supply chains in the paint manufacturing and retail industry constitutes a complex multi-level, cross-domain decision problem, with optimization objectives at each sub-system level. Research literature suggests the smart factory concept offers a viable solution at the production operations level. Agentic AI-driven capabilities logically extend to supporting the seamless orchestration of the last-mile distribution through stores and store-depot collaboration. However, it presents even more sophisticated opportunities by leveraging requirements from the entire supply chain ecosystem as an additional overall decision dimension, while dealing with the multitude of associated supply chain governance risks, including quality assurance, standard compliance, product traceability, information security, transparency, and explainability.

These agentic capabilities span the following domains: (i) autonomous sourcing and supplier collaboration, comprising negotiation dynamics, trust models, performance metrics, and collaboration strategies; (ii) quality assurance, compliance, and product traceability, encompassing quality standards, audit trails, auditing processes, data integrity, provenance, regulatory alignment, and risk indication; (iii) data ingestion and interoperability; and (iv) a dedicated agentic orchestration layer connecting decision agents with external systems of a enterprise resource planning/orchestration manufacturing execution system.

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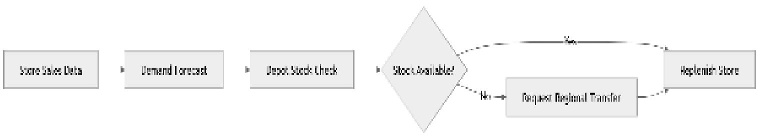
Graph 1 — Architecture layers maps all five structural tiers of the agentic supply chain framework: Data Ingestion → Quality & Compliance → Domain Agents (Manufacturing, Retail, Sourcing) → Orchestration → Governance. This reflects the paper's Section 3 architectural blueprint.

2.1. Autonomous Sourcing and Supplier Collaboration

The concept of agentic sourcing encompasses two related aspects of supply chain management that employ Agent Intelligence. The first aspect centers around supplier selection and negotiation processes that are autonomous or semi-autonomous. Negotiation partners are not limited to human decision-makers but include sophisticated software agents operated by either the buyers or sellers. These agents are responsible for autonomously handling supplier selection and for negotiating the terms and conditions of a contract. Typical attributes that such negotiations are expected to satisfy include price, lead time, and quality. Agent-based approaches include the creation of delegated agents that handle the negotiation process on behalf of their owners and resolve conflicts through the application of appropriate dispute resolution techniques.

Quality is a major concern in any supply chain, and negotiation algorithms can be extended to handle specific quality-related requirements and implications. In addition to price, lead time, and quality, appropriate criteria must be defined if the supply chain is to engage in recurring negotiations in an environment where the suppliers, prices, and demand are changing. Trust and trustworthiness modelling represent advanced features of knowledge-based CAP. Mechanisms for Trust and Reputation Management (TRM) in networks based on Diffusion and Electrostatic are also incorporated. Similarly, metrics that allow the supplier's performance to be assessed in terms of quality, lead time, and responsibility for service disruptions have been defined. Together with the criteria, the supplier's reputation can then be fed into the negotiation agents so as to enable Trust and Reputation Aware Negotiation. Another key innovation of this knowledge-based Agent Intelligence on CAP for Supply Chain Management is its Service-Centre Model.



Mathematical Formulas:

1. Demand Sensing & Forecasting (Section 4.1, 5.1)

Moving Average Demand Forecast:

$$\widehat{D}_t = \frac{1}{n}\sum_{i=0}^{n-1} D_{t-i}$$

Exponential Smoothing:

$$\widehat{D}_t = \alpha D_{t-1} + (1-\alpha)\widehat{D}_{t-1}, \alpha \in (0,1)$$

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Seasonal Demand Adjustment:

$$\widehat{D}_{t,s} = \widehat{D}_t \times S_s, S_s = \frac{\bar{D}_s}{\bar{D}}$$

where $S_s$is the seasonal index for season s.

2. Safety Stock & Inventory Optimization (Sections 3, 5.1)

Safety Stock Calculation:

$$SS = z \cdot \sigma_{LT} \cdot \sqrt{LT}$$

where z= service level z-score, σ_{LT}= standard deviation of demand, LT= lead time.

Reorder Point:

$$ROP = \bar{D} \cdot LT + SS$$

Economic Order Quantity (EOQ):

$$EOQ = \sqrt{\frac{2DS}{H}}$$

where D= annual demand, S= ordering cost, H= holding cost per unit.
3. Production Sequencing (Section 4.1)
Makespan Minimization (n jobs, m machines):

$$C_{max} = \min \max_j C_{j,m}$$

Job Priority Score:

$$P_j = w_1 \cdot \frac{1}{d_j} + w_2 \cdot \frac{r_j}{R} + w_3 \cdot q_j$$

where d_j= due date, r_j= remaining processing time, R= total resource capacity, q_j= demand urgency, w_i= weights.
Production Utilization Rate:

$$U = \frac{\sum_{j=1}^{n} p_j}{C_{max} \cdot m}$$

4. Supplier Trust & Reputation Model (Section 2.1)

Trust Score Update (Weighted Reputation):

$$T_i^{(t)} = \lambda \cdot T_i^{(t-1)} + (1 - \lambda) \cdot \frac{1}{K} \sum_{k=1}^{K} f_k\,(x_{i,k}^{(t)})$$

where λ= decay factor, f_k= performance function for criterion k(price, quality, lead time), $x_{i,k}$= observed metric.
Composite Supplier Score:

$$S_i = \sum_{k=1}^{K} w_k \cdot f_k(x_{i,k}), \sum_{k=1}^{K} w_k = 1$$

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5. Store-Depot Replenishment (Section 5.1)
Periodic Replenishment Quantity:

$$Q_{s,d} = \max\left(0,\ \widehat{D}_s \cdot T + SS_s - I_s^{(t)}\right)$$

where T= replenishment cycle length, $I_s^{(t)}$= current inventory at store s.

Cross-Dock Allocation:

$$A_{s,d} = \min\left(Q_{s,d},\ I_d^{(t)}\right)$$

where $I_d^{(t)}$= available depot stock.
6. Omnichannel Demand Shaping (Section 5)
Price Elasticity of Demand:

$$\varepsilon = \frac{\partial D/D}{\partial P/P} = \frac{\Delta D}{\Delta P} \cdot \frac{P}{D}$$

Optimal Promotional Price:

$$P^* = \arg\min_P [\text{Inventory Cost}(P) + \text{Stockout Penalty}(P) - \text{Revenue}(P)]$$

7. Agent Negotiation Utility (Section 2.1)
Multi-Attribute Negotiation Utility:

$$U_i(\theta) = \sum_{k=1}^{K} w_k \cdot u_k(\theta_k)$$

where $\theta = (\theta_1, \ldots, \theta_K)$are negotiation issue values (price, lead time, quality), $u_k$is the utility function for issue k.
Nash Bargaining Solution:

$$(\theta^*) = \arg\max_{\theta \in F} \prod_{i=1}^{N} (U_i(\theta) - d_i)$$

where $d_i$is the disagreement utility of agent i.
8. Supply Chain Risk & Resilience (Section 6)

Risk Score:

$$R_j = P_j \cdot I_j$$

where P_j= probability of disruption event j, I_j= impact magnitude.
Overall Supply Chain Risk:

$$R_{total} = \sum_{j=1}^{M} R_j = \sum_{j=1}^{M} P_j \cdot I_j$$

Service Level:

$$SL = P(D \leq I + SS) = \Phi\left(\frac{SS}{\sigma_D \cdot \sqrt{LT}}\right)$$

where $\Phi$is the standard normal CDF.

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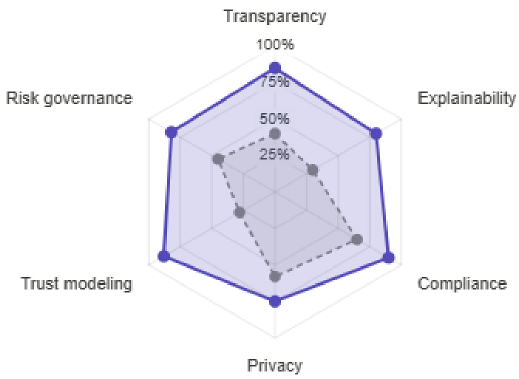
III. ARCHITECTURAL FRAMEWORK FOR PAINT INDUSTRY ECOSYSTEMS

Paint manufacturing and retail supply chains typically consist of a large number of active partners, and relationships extend across multiple tiers — for raw materials, for packaging materials, and among contractors and toll manufacturers. Sourcing is further complicated by a longer list of quality standards that may differ for each supplier. The requirement for timely delivery at the lowest landed cost is challenged by compliance verification at multiple levels, including origin testing for pigments, volatile organic compound limits for emulsions, iso-grade specifications for solvents, and chemical–physical properties for finished products. Evidence of traceability must also be maintained. Regulatory positions of the various countries may differ broadly, and they evolve continuously following changing environmental and ecological requirements. As a consequence, the required amount of data from suppliers shoots up rapidly, but validation and verification follow cumbersome paths in supply chain operations. Various categories of partners favour periodical audits followed by real-time assurance. Flows of critical quality parameters do not match a smooth flow distribution. Failures or near-misses emanating from Particular partners call for targeted investigation.



Graph 3 — Supply chain flow traces the full paint ecosystem from raw material suppliers (pigments, solvents, packaging, chemicals) → paint factory → regional depots → dealer stores/D2C → consumer, with the real-time demand sensing signal looping back. The store↔depot collaboration arc and the quality layer spanning all tiers both come directly from Sections 5 and 3.

3.1. Data Ingestion and Interoperability

A smart supply chain ecosystem creates an efficient mechanism for improving business outcomes by coordinating supply chain partners with the use of agentic AI and process orchestration. Interoperability plays a crucial role in enabling bi-directional data flow among Supply Chain Planning components and partner nodes. Data sources and formats need to be identified to ensure that all TCPs can ingest enterprise data for planning and fulfilment. Data quality management and semantic mapping are critical to enable accurate insights.

Key business processes require stakeholder involvement to align decision objectives, planning assumptions, orchestration workflow, and operational plan revisions. Data exchange between TCP and supply chain partners requires continued interaction to fulfil specific needs, such as defining static demand shaping rules or addressing demand–supply imbalances across channels. Demand signals and fulfilment constraints are ingested on an ongoing basis, with compliance checks to maintain share and service levels. Suppliers share production schedules, confirming requests and delaying or preponing orders where feasible.

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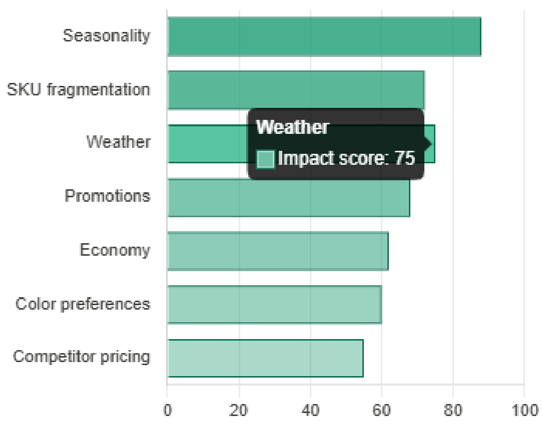
Supply Chain Challenge	Traditional Limitation	Agentic AI Solution	Business Benefit
Seasonal demand variation	Static forecasting	Real-time demand sensing	Improved forecast accuracy
Supplier delays	Manual coordination	Autonomous supplier negotiation	Reduced lead time
Overstocking	Fixed safety stock	Dynamic inventory optimization	Lower inventory cost
Production bottlenecks	Sequential planning	AI-driven sequencing	Higher throughput
Store replenishment delays	Manual scheduling	Autonomous replenishment agents	Better shelf availability
Compliance verification	Periodic audits	Continuous compliance monitoring	Reduced risk

IV. AGENTIC CAPABILITIES IN MANUFACTURING

Sequencing and scheduling of manufacturing processes are crucial for effective orchestration of overall supply chain flows. At the operational level, the sequencing logic must consider the specific characteristics of every product and each production run, as well as the available resources (bottlenecks) in the production environment. The likely presence of preemptive production changes implies constraints that are highly dynamic, changing frequently and possibly at short notice, therefore requiring a fast-response approach. Moreover, high-frequency production flows between plants require continuous consideration of demand signals to be represented as accurately as possible (for those plants with very specific products) and are also a major driver for highly preemptive production scheduling. An agentic AI-enabled system improves the speed and quality of production sequencing while addressing these requirements.

Dynamic Production Sequencing. The decision agent in charge of production sequencing aims to identify the process sequence at every single time frame or specific decision moment. Although the decision-making support incorporates the existence of service-level constraints in terms of maximum service-level unfulfilled orders and required delivery dates, it does not assure adherence to those thresholds. Whenever a service level is not fully within the operational strategy, it may penalize parts of the decision-making model. For a specific time frame, the decision agent assesses the demand signals (in terms of quantities, timing, and locations—demand). It considers the constraints of required processes (products and flows) and analyzes the production environment to be sequenced (bottlenecks) and its specifics (input availability and timing, output flows, and available resources). It then processes the information and applies the built-in sequencing logic.



Graph 4 — Production sequencing decision flow models the paper's Section 4 agent logic: four input signal types feed the production sequencing agent, which applies sequencing logic, checks service-level constraints, either releases an optimised plan to MES or resequences with penalties, and triggers demand shaping downstream.

4.1. Dynamic Production Sequencing

The manufacturing processes behind most consumer products are designed for efficiency at scale. These processes are very effective in managing average demand for product. Nevertheless, demand patterns are seldom constant and user preferences keep changing. For example, in the paint industry demand for different finishes, shades and quality depends on the weather and is also affected by promotions. Demand shifts are often not accounted for in the models used by factories for scheduling production. Demand shaping at the retailer allows prediction of the types of products required,

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but not the exact volume. Since the production capacity of individual lines depends on the order combination, production scheduling needs to incorporate all these variables. Agentic capabilities in manufacturing operations allow automated tuning of production schedules to meet demand signals from the market.

Contextualized Capabilities have been defined earlier as that part of the Layers of an Architecture framework that is specific to the factory making a product or family of products. These include the Product Definition, Product Data Management, Business Driven Resource Management and Production Logic. The production-sequencing logic defines the ordering of product that maximizes production efficiency while adhering to the capacity constraints within the factory.

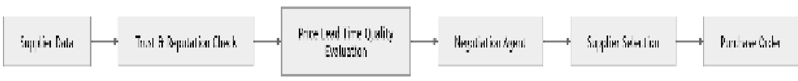
Table 3: Autonomous Supplier Collaboration Metrics

Metric	Description	Measurement Unit	Impact
Supplier Trust Score	Reliability of supplier	Score (0–100)	Better sourcing decisions
Lead Time Accuracy	Delivery schedule adherence	Percentage	Reduced disruptions
Quality Compliance Rate	Adherence to quality standards	Percentage	Improved product quality
Negotiation Success Rate	Successful autonomous negotiations	Percentage	Faster procurement
Service Disruption Index	Frequency of disruptions	Count/month	Risk mitigation
Reputation Score	Historical supplier performance	Weighted Score	Trust-aware sourcing

V. AGENTIC CAPABILITIES IN RETAIL AND DISTRIBUTION

Last-mile fulfillment in retail and distribution continues to present a complex challenge for the paint manufacturing and retail ecosystem. Multiple players, including retailers, distributors, and manufacturers, are involved in the replenishment of retail shelves to ensure product availability. In addition, the overall replenishment process at both the depot and store levels is becoming increasingly complex because distribution centers and depots are performing in-store replenishments and fulfilling direct-to-consumer orders. Open cross-docking in depots is also gaining traction. Nevertheless, none of these initiatives are being coordinated at an agentic level; while physical flow is being managed, information about product availability is not being shared across silos.

Four questions thus arise: How can last-mile replenishment be orchestrated more effectively? How can the collaboration between stores and depots be improved for replenishment across these points? What mechanisms can be implemented to influence demand composition across different channels? How can omnichannel pricing be aligned with demand-shaping promotions? A first step towards addressing these issues is the development of last-mile orchestration capabilities. These are further augmented with agentic collaboration between stores and depots in the replenishment process; demand shaping across different channels; and the alignment of omnichannel pricing with demand-shaping promotions. Retail fulfillment orchestration at the store level focuses on the identification of orders that are held in the fulfillment queue for the longest time without generating free-to-sell inventory. When store deliveries are running behind schedule, shelf replenishment queues are prioritized. Collaboration between stores and depots is facilitated whenever a depot is within a predetermined distance of the store. Demand shaping considers price promotion signals, direct-to-consumer fulfillment constraints, and the optimal price setting for demand-shaping promotions.



VI. GOVERNANCE, RISK, AND ETHICAL CONSIDERATIONS

Transparency, Explainability, and Trust Models: Transparency, risk governance, and ethical responsibility are essential aspects of effective supply chain management, particularly when AI and autonomous agents are involved. Explanation of the rationale behind decisions taken by intelligent systems and processes is crucial in establishing trust with affected stakeholders. Media reports of AI hallucinations highlight the inherent risk of relying on generative AI. In high-stakes use cases, stakeholders may demand explanation of AI-created content before granting permission for its use. Risk

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governance becomes even more critical with the creation of intelligent agents. Trustworthy business interactions with autonomous AI agents require assurance that the AI agent interacts only with trusted partner agents, that its decisions are correct, and that it acts according to expected standards of behavior. Confidence in intelligent systems is also enhanced by a communication strategy that actively explains agent policies and key decisions when interacting with humans.

Security, Privacy, and Compliance: Security, privacy, and compliance must be addressed in any system dealing with product manufacturing, storage, distribution, and replenishment. Threats and vulnerabilities should be identified by a suitable threat modeling technique. Privacy controls should be implemented per applicable regulations based on data used to manage sensitive aspects such as customer profiles and demand patterns (e.g., GDPR). Data retention and disposal policies should ensure that sensitive data is deleted when no longer needed. Access controls should be defined based on users' roles in the system and relevant security policies. Compliance with national and regional laws governing company operations is particularly relevant with respect to product labeling, product safety, and business ethics.

Table 4: Agentic Manufacturing Sequencing Parameters

Parameter	Description	AI Consideration
Production Capacity	Available machine capability	Dynamic allocation
Setup Time	Time between product changes	Sequence optimization
Demand Priority	Urgency of orders	Demand-driven scheduling
Safety Stock	Inventory buffer levels	Adaptive adjustment
Bottleneck Resources	Constrained production points	Bottleneck balancing
Delivery Deadlines	Customer fulfillment targets	Service-level optimization

6.1. Transparency, Explainability, and Trust Models

Transparency and explainability are critical requirements to foment trust enabling participation among the various stakeholders in a paint manufacturing supply chain ecosystem, as their actions affect multiple parties. While the execution of functional plans is usually governed by business procedures, the means employed for their execution may be less clear to stakeholders. Explainability is, in fact, a crucial aspect of AI application because it allows for recognition of decision bases and corrective action recommendation. The issues raised by explainability in AI applications are recognized and studies suggest approaches to it. Since they are developed and executed under AI supervision, key agent decisions may require explanation such as which safety stock and forecasting mechanisms are used, why a production sequence was adopted concerning performance metrics, why a depot–store replenishment plan diverged from established practice, and—finally—why a specific store depot reshaping action is suggested and to whom.

Trust in the recommendation base is also important since these models' performance may influence a stakeholders' constituents, such as a partner quality audit team, a channel aligned for promotion implementation or simply the outside legal body in demand of compliance information. Trust models provide a formal mechanism to foster trust among negotiation participants. Their structure is flexible to allow any trust-concerned aspect to be included and tuned according to the needs of the negotiation process. These aspects are expressed as variables whose maturity is related to trust or distrust interaction dynamics. The model defines how the overall trust or distrust is dynamically updated from trust interactions among the participants.

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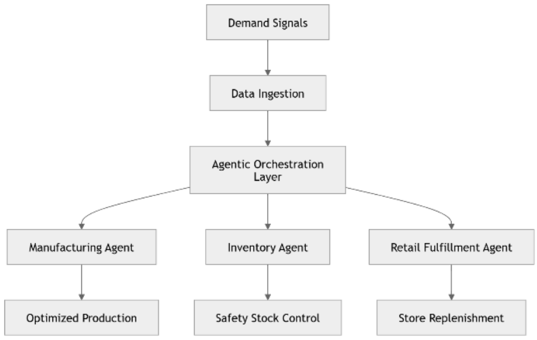

VII. CONCLUSION

Agentic AI technology enables smart supply-chain orchestration by its self-learning, self-improving, and self-interactive decision-support capabilities in supply-chain-normalization environments. It allows industrial ecosystems to build a semantic-level-interoperability platform for long-term collaboration, with a decentralized-orchestration governance model. A standardized paint-management model is first established, covering the extended supply chains, before the explicit main issues are identified. Agentic AI orchestrates normalization, spokes and hubs establish their agentic, self-learning, dynamic, and event-triggered production/supply ability, and the decentralization of last-mile fulfillment and omnichannel supply can definitely meet omnichannel demand with the least risk.

Beyond the norms or standards of the enterprise, a semantic-level paint-management model paves the way for supplier integration, risk-sharing collaboration, omnichannel demand shaping, and fulfillment orchestration. The development of supporting cognitive-agent technology for extended-supply-chain missions overcomes the decade-ongoing gap of cyclical deployment of advanced analytics within normal operations. Future work resides in the co-creation of data at the paint-tech level to improve the normal operation of the industry ecosystem.

Table 5: Store-Depot Collaboration Framework

Process	Depot Role	Store Role	Agentic AI Capability
Inventory Replenishment	Dispatch stock	Monitor shelf levels	Autonomous replenishment
Demand Forecasting	Aggregate regional demand	Provide local demand signals	Predictive analytics
Cross-Docking	Redirect urgent inventory	Receive fast-moving goods	Dynamic routing
Promotion Management	Allocate promotional inventory	Execute campaigns	Demand shaping
Emergency Transfers	Reallocate stock between depots	Trigger shortage alerts	Intelligent orchestration

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