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IntelliChain Automotive: Embedding Machine Cognition into Dispersed Supply Logistics Networks within Industry 4.0 Operational Boundaries

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Abstract

Digital transformation in automotive supply networks—typically characterized by Just-in-Time principles and high-risk vulnerability to shocks—enables predictive logistics: a predictive-prescriptive-optimization-enhanced real-time decision-support paradigm spanning demand forecasting, inventory optimization, transportation planning, and capacity network design. Supply networks supporting Industry 4.0 detect, analyze, and respond rapidly to changes, disruptions, and stresses, in the process minimizing total cost of ownership while improving lead-time and service-level targets predicted with a digital twin. Data ecosystems capture, aggregate, analyze, and disseminate data streams generated by a network's partners employing standardized discrete-event, agent-based, and machine-learning models, deployed within ultra-responsive edge cloud and fog architectures.

Despite long-standing research interest, relatively few predictive-logistics applications exist, signaling a gap that demands investigation. Evidence presented here addresses an objective defined through literature synthesis: Explore Industry 4.0 drivers and constraints while assessing the impact of emerging Industry 4.0 capabilities on predictive logistics for distributed automotive supply networks. Key findings illustrate the performance benefits of predictive-logistics in two empirical cases describing automotive semiconductor supply chains and electric vehicle battery and component logistics.

Keywords: Artificial Intelligence, Predictive Logistics, Supply Chain Management, Distributed Automotive Networks, Industry 4.0, Edge Computing.

1. Introduction

The trending concepts that surround Industry 4.0 and promote the digital transformation of supply chains associated with the automotive industry in recent years, have transformed the automotive semiconductor supply chain. The emergence of the pandemic accelerated a new wave of shortages affecting automotive vehicles proportional recovery. Companies connected with the industry developed actions to prepare and mitigate a crisis in the supply chain, based on actions by local suppliers and development of risk-mitigation receipts with alternative suppliers in different regions.

Concerning Electric Vehicles using lithium-ion batteries, the supply and logistics structure also face challenges of performance, resilience and total cost of ownership with durability of supply during the life cycle. Electric vehicle batteries life cycle base considers diversified suppliers located in different regions from the automobile manufacturers, contributing to improved performance, reduced total cost of ownership, increasing supply resilience, and major safety concerns with transport across countries connected by a waterway of risk supply, also of approval of Simulated Transport in a Circular Economy. The analytics are complemented with models to optimize the logistical flows of semifinished and finished products throughout the supply chain. These models consider constraints such as transport availability, network capacity, or safety stock levels, with the aim of minimizing the total cost while keeping the service level as high as possible.

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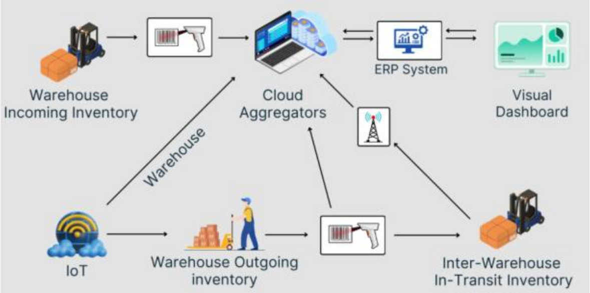


Fig 1: AI-Powered Applications are Redefining Logistics and Supply Chain Management

1.1. Background and Significance

A state-of-the-art automotive semiconductor supply chain case reveals how risk mitigation through diversified sourcing speeds recovery and alleviates future risk, while a second focused on logistics for electric vehicle battery and component sourcing demonstrates how predictive logistics boosts performance in EVs—an area yet to benefit both from distinct AI trading models and large-scale Industry 4.0 digital-twin platforms.

Both empirical cases highlight how predictive logistics can be steered toward Industry 4.0 objectives, notably data sharing for privacy-focused computing along mobility-data governance principles. Industry 4.0 horizons appear to promise predictive logistics a growing development trajectory, with implications for the design of data-sharing ecosystems across large automotive networks that preserve operational, industrial, and corporate privacy while creating enough trust to lift practice beyond the large-automaker-led business-as-usual.

Equation 1: Core variables (used across the paper's metrics)

Let:

- $t = 1, \dots, T$: time periods (days/weeks/months)
- D_t: actual demand in period t
- $\widehat{D}_t$: forecast demand in period t
- $e_t = \widehat{D}_t - D_t$: forecast error
- L: replenishment lead time (in periods)
- μ_L, σ_L: mean and std-dev of demand *during lead time*
- R: reorder point
- SS: safety stock
- z: safety factor (standard normal quantile)
- CSL: cycle service level (probability of no stockout during lead time)
- TCO: total cost of ownership

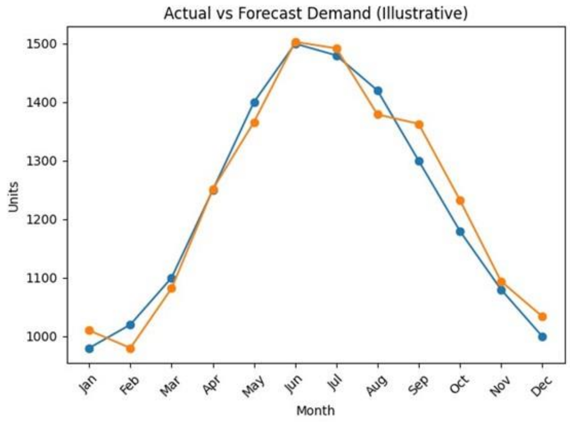
These map directly to the paper's performance view (Accuracy/Lead Time/Service Level/TCO) and its model scope (forecasting, inventory, transportation, network optimization, multi-objective optimization).

2. Conceptual Foundations

Building on these considerations, the second section of the manuscript establishes the conceptual foundations of the investigation. First, it summarizes insights gathered from the literature documenting the ongoing shift toward Industry 4.0 and the digital transformation of logistical processes embedded in automotive supply chains. Then, it goes on to define predictive logistics, delineate its intended scope, and identify the metrics necessary for assessing predictive-logistics performance.

2.1. Industry 4.0 and Digital Transformation in Automotive Supply Chains

The concept of Industry 4.0 has arisen from an extensive body of literature and diplomatic and policy narratives; without attempting to survey any of these discussions, four central themes emerge: (1) Digital transformation supported by ubiquitous connectivity, lossy sensors, and advances in machine learning as drivers of new business models, value propositions, and ecosystems; (2) The digital twin of the enterprise (the virtual representation of an organization's physical systems, capabilities, processes, and its associated ecosystem) that drives simulation, current-state awareness, scenario analysis, and resilience; (3) Interoperability standards for systems, processes, and supply chains (including Industry 4.0 reference architecture, maturity models, digital security, and Privacy by Design); and (4) The position of governments and society in the ecosystem, where the creation of high-impact policies and regulations that ensure a globally coherent and aligned ecosystem creates an enabling environment for individual actions.



2.1. Industry 4.0 and Digital Transformation in Automotive Supply Chains

Industry 4.0 concepts encompass the Internet of Things (IoT), cyber-physical systems (CPS), digital twins, autonomous agents, and synergies from agent localization for monitoring, processing, and decision-making. Designed to be smart, connected, and collaborative, automotive and electric vehicle (EV) supply chains leverage Operations Technology (OT) and Information Technology (IT) convergence. Developing, manufacturing, and regulating road vehicles requires unprecedented coordination across stakeholders. Industry 4.0 technologies, together with interoperability standards for products, processes, and authority control, enable the digital transformation of vehicle supply chains at virtually all maturity levels—from facilitating data exchange across browsers and devices to create automatic, physically controllable representations of dynamics.

Four domains characterize the digital transformation of vehicle supply chains. First is the vision of next-generation electric and hydrogen-powered road vehicles, from conception to recycling. Second is the custom electric and hydrogen supply chain of supporting jurisdictions, implementing data-based services and auxiliary vehicle management. Third is the evolution of supply chains providing elements to the ICE-shifting vehicle manufacturers, covering growing uncertainties with predictive logistics. Finally, next-generation sensors, artificial intelligence differentiators, risk-based models of emerging variables, and digital-twin ecosystems act at all levels of vehicle and support jurisdiction custom chains. This digital transformation contrasts with traditional supply chain management—supply-driven, capital-intensive, locally embedded, high-TCO, bilateral, and underpinned by fixed business models—by enabling responsive, Connected Customer Chains.

2.2. Predictive Logistics: Definitions, Scope, and Metrics

Predictive logistics comprises integrated models, methods, and systems that deliver accurate future information on an automotive supply chain to improve — compared to traditional approaches — three decision-making aspects: planning and scheduling ahead in time, considering longer lead times, planning beyond local optimum, and sharing information, risk, and cost. Three specific types of decisions are considered: forecasting demand and seasonality; product mix; and inventory deployment. The first type affects all links in the supply chain; it identifies demand signals and conveys them to the suppliers. The second type affects the manufacturers of the end product; it identifies the seasonality effect and anticipates the product mix over an appropriate time horizon. The third type is about planning the inventory of all intermediate products; it allows for anticipating replenishment orders and ensures sufficient cover throughout the supply chain.

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Predictive logistics relies on a precise flow of interconnected models equipped with rich embedded knowledge. For this mineral-based predictive analytics framework to improve decision making, many deadlines need to be met. First, the demand signal must be as accurate and advanced as possible. Second, the marketing departments of the manufacturers require the seasonal and product mix decisions in due time to plan their manufacturing programs accordingly. Third, the inventory of the core products must be large enough to absorb the lead time of the replenishment orders and to cover the sales forecasts with a specified service level. Predictive logistic analytics enhance three decision-making aspects: planning and scheduling further in advance than the actual lead time; considering long-term capacities; moving from point to network optimization; and sharing risks and costs across the entire automotive semiconductor supply chain.

Equation 2: Forecast Accuracy equations (demand forecasting)

2.1 Error definition

$$e_t = \widehat{D}_t - D_t$$

- Positive e_t: over-forecast
- Negative e_t: under-forecast

2.2 MAE (Mean Absolute Error)

Step-by-step

1. Absolute error each period:

$$|e_t| = \left|\widehat{D}_t - D_t\right|$$

2. Average over T periods:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|e_t|$$

2.3 RMSE (Root Mean Squared Error)

Step-by-step

1. Square errors:

$$e_t^2 = \left(\widehat{D}_t - D_t\right)^2$$

2. Mean squared error:

$$MSE = \frac{1}{T}\sum_{t=1}^{T} e_t^2$$

3. Root:

$$RMSE = \sqrt{MSE}$$

2.4 MAPE (Mean Absolute Percentage Error)

Step-by-step

1. Period APE:

$$APE_t = \left|\frac{\widehat{D}_t - D_t}{D_t}\right| \times 100$$

2. Average:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} APE_t$$

(These are common “Accuracy” measures used to quantify the forecasting component the paper discusses.)

3. Architectural Framework for Distributed Automotive Networks

Within the context of predictive logistics in distributed automotive supply networks, the architecture encompasses stakeholders, data ecosystems, and data infrastructures that enable predictive logistics capabilities. Such predictive logistics infrastructures furnish decision-makers with complete and precise foresight into future developments affecting supply chain performance. Capable of analyzing current conditions and of predicting future developments through the simulation of individual decisions across the network, these infrastructures facilitate anticipatory adjustments that enhance supply chain performance.

Manufacturers, suppliers, logistics providers, customers, and regulators fulfill specific roles within predictive logistics infrastructures. These infrastructures generate structured data that reveal current states and anticipate future developments. The ownership and flow of data vary depending on predictive logistics design choices. For related stakeholders within each infrastructure, the governing orders determine the degree of openness and how relationships operate. Trust, accountability, and incentives underpin successful data governance. Industry groups and associations play pivotal roles in creating the required data-sharing foundations.

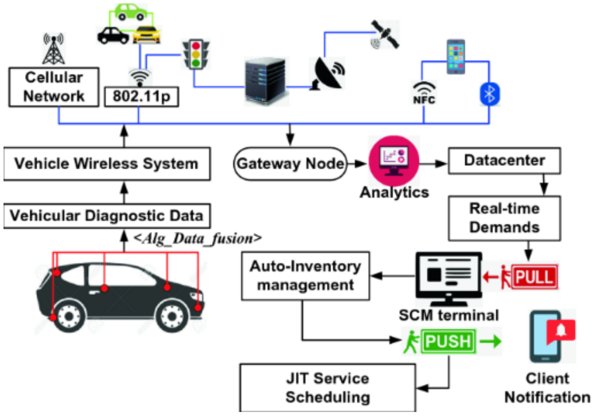

Fig 2: Architectural Framework for Industry 4.0 Compliance Supply Chain System

3.1. Stakeholder Roles and Data Ecosystems

The architecture for predictive logistics in distributed automotive supply networks depends on demand signals from OEMs or Tier 1 suppliers that indicate product requirements over time. Inputs for data ecosystems include historical demand patterns, forecasted supply constraints and lead times, inventory positions, transportation capacities, costs and risk profiles, and models of product seasonality and discontinuity. Ownership of the underlying datasets usually lies with the party supplying the data; third-party providers may aggregate data across multiple participants for value-added services. However, a lack of trust stems from natural data asymmetries. Data-sharing agreements enforced by trusted entities can help mitigate this concern.

An elementary data ecosystem connects OEMs or Tier 1 suppliers with one or more logistics service providers; for instance, logistics partners may be assigned different segments of a supply chain, such as inbound logistics or the transport of finished products. More advanced ecosystems support multiple OEMs or suppliers sharing their demand forecasts with common carriers and their semiconductor production partners. Such consortiums address the forecasted shortage in automotive silicon by pooling and optimizing (or at least coordinating) shipments of semiconductor components during highly constrained periods. Although risk-sharing and cost-reduction opportunities may exist, gaining agreement among participants is challenging; hence, early versions focus on risk mitigation.

3.2. Data Infrastructures: Connectivity, Standards, and Interoperability

To facilitate advanced data sharing, partner organizations must establish common frameworks for data capture, communication, integration, and persistence. Essential aspects of such data infrastructures include the readiness of supply-chain partners to connect and exchange data, the agreed protocols and standards for such exchanges, and the standards by which the novel data ecosystem is rendered secure and trustworthy.

Connectivity and Data Integration. Supply-chain organizations differ widely in their readiness (technological, organizational, and process-wise) to connect with other partners for data sharing and collaboration. Vulnerabilities and their severity shape priorities for investment in communications readiness, with a first focus on essential connections to high-risk business partners (Fugate et al. 2010). Such considerations are critical in determining the resources needed to support connectivity with partners, especially local logistics service providers or public transport infrastructures that require formal investment plans and resources but represent low-cost options for computing service provisioning. A connectivity readiness model helps organizations assess their deployment priorities and related security aspects across the different types of peers present in the supply chain. Given the growing number of connectivity incidents affecting supply chains around the globe, organizations are advised to implement strict cyber security guidelines based on sound risk assessment.

Communication Protocols and Interoperability Standards. Fast and secure data exchange makes it possible to foster a richer and more powerful horizon for integrated day-to-day operations and schedule management. Organizations need to agree on the communication protocols in use and related APIs to guarantee data exchanges and system integration. Interoperability standards (e.g., data formats and exchange protocols) not only reduce the time, cost, and risk of data integration but also pave the way for smoother operations across partners. The adoption of sector-specific interoperability standards can significantly ease the effort involved in joining a data-driven ecosystem. The Digital International Data Space proposal and other similar initiatives aim to establish a secure and trustworthy data space for industry, public institutions, and research across sectors and geographies.

Cybersecurity Baselines for Data Sharing. Data-sharing initiatives in which data is exchanged across partners create new risks and vulnerabilities that need to be carefully assessed and monitored throughout the lifespan of the collaboration. Uncontrolled data sharing can reduce the value and quality of the data being exchanged and erode mutual trust between partners. Supply chain organizations need a clear policy framework to assess compliance with external regulations, safeguard the confidentiality of customers and business partners, and prevent breaches of trust among peers. Data governance controls should include data-sharing agreements, risk assessment procedures, audit trails for data usage, and the delegation and monitoring of specific controls on sensitive data categories.

4. Predictive Models and Methodologies

Essential predictive models span demand forecasting, product seasonality studies, product mix predictions, inventory optimization, transportation planning, network design, network routing under constraints, and multi-objective optimization. Within each category, critical decisions involve the choice of modelling approach and metrics for monitoring predictive performance and evaluating trading strategies. All models share a common theme: provision of owners' decisions regarding the risk, cost, or service level of fulfilment. Predictive accuracy relates primarily to the accuracy of these owners' decisions, while service lead times, service level, and total cost of ownership are derived from overall logistics performance measures. The monitoring of these broader metrics recognizes an interdependent ecosystem in which owners, suppliers, logistics providers, and enablers each determine their part of the cycle.

Demand forecasting encompasses individual or total product demand, product seasonality, and product mix distributions across different stakeholder bases. A wide range of statistical, machine learning, and hybrid approaches exists, and the selection of approach aligns most particularly with the characteristics of the underlying data. Essential components are the sources of data, their availability and accessibility, and the trading strategy of the stakeholders involved. Performance monitoring focuses primarily on the prediction of demand at the fulfilment-owner supplier interface, as this is the source of all customer demand signals. The evaluation of performance is, however, more complex: it must not only ensure that the fulfillment owners can act accordingly but also assess the decisions of other stakeholders related to capacity and inventory provisioning.

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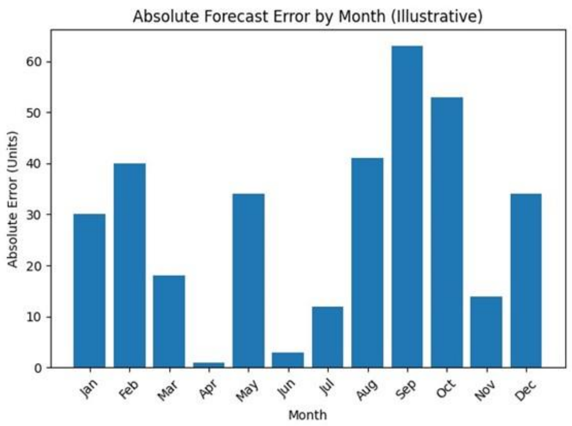

4.1. Demand Forecasting and Inventory Optimization

Models for demand forecasting, seasonality, product mix, and inventory optimization are essential components in the predictive logistics paradigm. Demand signals for a given manufacturing facility are shaped not only by seasonal characteristics and product mix but by macroeconomic factors, industry trends, and finally external shocks such as the COVID-19 pandemic. Therefore, predicting demand during a material shortage phase is far more complicated due to uncertain external signals from major customers. Other factors must be considered, such as provisioning alternative manufacturing capacities during the shortage/supply shortage to fulfil potential signals and putting a complete supply chain risk mitigation strategy in place together with the risk management plan.

Because of the demand volatility caused by high-mix/low-volume automotive production systems, and numerous call-offs across a part portfolio, many automotive OEMs have been struggling with inventory holding levels for their low-mix semiconductor Electronic Control Units (ECUs). Some manufacturers have adopted a statistical or heuristic approach to estimate the seasonal pattern of shortages by product family and applied a simple custom Kore column method to improve the forecast accuracy. Others have planned budgets using a system dynamics model which examines the interaction between an Automotive OEM, several Tier 1 Semiconductor Suppliers, their fabrication plants (fabs), and external wafer & packaging foundries. The model incorporates stock-outs and lead times into a dynamic feedback loop and is particularly geared toward contingency planning for chip shortages, but Hung's focus lies more in demand-supply planning rather than predictive logistics. Demand and shortage forecasting of EV battery supply chain has combined machine learning with time-series technology.

Equation 3: Lead time + inventory deployment equations (Service Level + cost)

3.1 Demand during lead time

If per-period demand is random, the lead-time demand is:

$$D_L = \sum_{i=1}^{L} D_{t+i}$$

If demand per period is i.i.d. with mean μ and std-dev σ:

$$\mu_L = L\mu, \qquad \sigma_L = \sqrt{L}\sigma$$

3.2 Reorder point policy (base-stock / (R, Q)-style logic)

A standard reorder point:

$$R = \mu_L + SS$$

3.3 Safety stock from a target service level

If lead-time demand is approximately Normal:

$$SS = z\sigma_L$$

So:

$$R = \mu_L + z\sigma_L$$

3.4 Cycle service level (probability of no stockout during lead time)

By definition:

$$CSL = P(D_L \leq R)$$

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Standardize:

$$P(D_L \leq R) = P\left(\frac{D_L - \mu_L}{\sigma_L} \leq \frac{R - \mu_L}{\sigma_L}\right)$$

Since $R - \mu_L = z\sigma_L$:

$$CSL = \Phi(z)$$

where $\Phi(\cdot)$ is the standard normal CDF.

This directly links **Service Level** to safety stock (and therefore to cost/TCO).

4.2. Transportation and Network Optimization

Models for transportation planning and network optimization focus on the practical realization of the transportation flows specified in the demand/transportation forecasts and generally have one (or more) of the following objectives: operational workflow optimization, fleet size/capacity planning, and/or network design. Additional related problems include the planning of pick-up and final delivery routes, the operational execution of flows under constraints, and multi-objective design combining total distance/cost minimization with risk hedge against disruptions.

Transportation planning and monitoring can also consider the influences of seasonality and price volatility. Transportation costs depend on available highest/lowest capacity and truck price/availability seasonality over a year. Advanced planning systems can integrate and combine data on transportation price difference by country for the company’s products (e.g., for export to electric vehicle parts/components supply chains) or by transport type and season with prototype shipping costs for other products to create temporal feedback data; these feedbacks will indicate changes in cross-border shipping price differences and in the price difference between suppliers in different countries.

Network design can consider expected transport lead times and expected costs, both from past statistics and from open online data (e.g., for USA–China–Europe cross-border transport) as well as the forecast distribution of the total quantity delivered by each supplier. Scenario analysis is crucial not only for network design but also for other planning tasks, since a specific planning design will not guarantee resilience in a disrupted reality. For these reasons, an analytical Transport Network diagram may focus on migration risks between countries (e.g., due to health/environment issues) and the associated risk-cost analysis. Resilience-oriented scenario analysis of maritime transport routes can include temperature conversion speed and seasonality (for magnetic components transport) as extra transport cost-driving factors; traffic-jam season and actual status can also be integrated into scenario planning for testing routing robustness.

5. Constraints and Enablers in Industry 4.0 Context

Automotive-industry-specific data ecosystems face data-governance, privacy, and risk challenges. Predictive logistics generates and shares sensitive information, with potential legal, commercial, and reputational implications. The associated health data belong to the patient; machine data to the manufacturer; and driving behavior data to the driver. Consequently, the definition of use-cases determines data ownership, access rights, and restrictions. Governance establishes policies for non-discriminative data sharing; misuse protection; risk assignment; third-party data access; and harm mitigation. Indeed, trust is crucial for partnerships among competitors and complementary players in data marketplaces supported by commercial agreements.

Design policies comply with laws (e.g., GDPR), maps compliance obligations, assesses risk exposure, and tailors’ data-sharing agreements. Anonymization removes identifiers, and access-control systems enforce compliance. Audit trails log and monitor actual sharing. Anti-cybercrime policies, assessment frameworks, and baselines support data sharing networks. Various models, standards, and recommendations (e.g., NIST Cybersecurity Frameworks, ISO/IEC 27001:2013) apply. Connectivity and integration in distributed data ecosystems depends on these infrastructures.

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Edge-computing architectures that incorporate distributed intelligence minimize latency by processing data closer to their origin. This preserves bandwidth and confidentiality while enabling local, rapid, and autonomous decisions for time-sensitive applications. Deployment across every partner is challenging because not all operations have a valid business case, and facilitating inter-partner decision-making raises governance issues, especially in a competitive environment.

Such an approach entails redefining the roles and responsibilities of the different players within the ecosystem. Several parties can undertake the distribution of these capabilities. The key factor shaping the decision looks like the level of trust in relationships. Very hierarchical ecosystems, characterized by a high asymmetry between dominant and less powerful members, will typically centralize the distribution of edge intelligence in the hands of the strongest player; ecosystems based on regular collaboration and cooperation will distribute such capabilities autonomously, while ecosystems with very loose partnerships will leave this distribution to an ad-hoc basis.

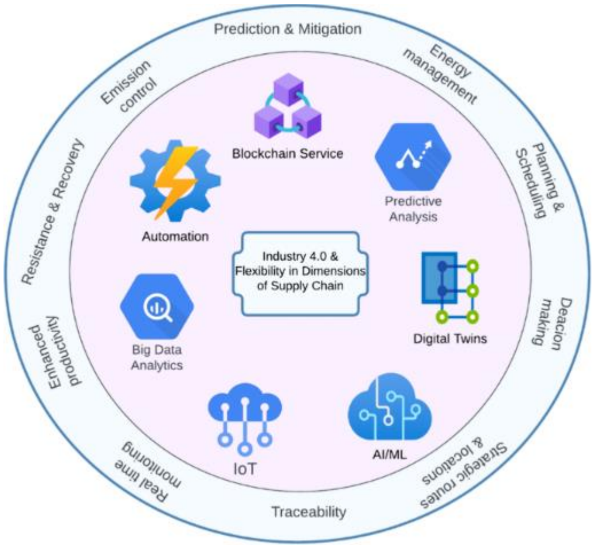


Fig 3: Analyzing Industry 4.0 Adoption Enablers for Supply Chain Flexibility

5.1. Data Governance, Privacy, and Security

Data governance involves policy choices concerning the generation, management, and exploitation of data. These decisions require a risk-based approach to privacy and security, grounded in a thorough evaluation of the usefulness of data-sharing, the potential for harm to society, and the capacity of proposed measures to prevent such harms. Data-sharing agreements define risk ownership and transference among parties. Data privacy legislation governs personal-data processing and sharing. Data security is a set of controls protecting the confidentiality, integrity, and availability of data throughout its life cycle.

Risks to data privacy and security need to be assessed in relation to the expected benefits from data-sharing. Not all data need to be shared, and not all data need to be shared in an identifiable form. Anonymization is often a good solution, but it should not be relied upon entirely, since there are well-documented cases of re-identification. Where personal or other sensitive data are shared, risk transference is usually the appropriate solution. The parties should carefully document the purpose and procedure for data-sharing and conduct regular audits to demonstrate compliance. Data-sharing agreements should also include adequate security provisions.

5.2. Edge Computing and Distributed Intelligence

Computing and intelligence are gradually being moved from centralized cloud facilities to the “edge” of the network. Logistics processes must become more autonomous to reduce the latency in decision-making required for tactical and operational effects. Edge computing encompasses hardware, software, networks, algorithms, and security mechanisms that allow computation to be placed closer to the data source. By distributing demand forecasting, production and logistics planning, and, ultimately, inventory and transport optimization across the supply chain ecosystem, reliance on a centralized cloud is reduced considerably and local actors can process information generated in their vicinity. However, the actual logistical decisions are not made locally. Instead, edge intelligence supports routing, emergency planning for repairs and replacements, and local risk assessment while the guidance, monitoring, and risk mitigation of the overall process remains in the cloud.

Equation 4: Total Cost of Ownership (TCO) equation (linking forecasting → inventory → transport)

A standard operational TCO decomposition over horizon T:

$$TCO = C_{proc} + C_{hold} + C_{trans} + C_{stockout} + C_{expedite} + C_{risk}$$

Where (typical forms):

4.1 Procurement / production cost

$$C_{proc} = \sum_{t=1}^{T} c_u \, x_t$$

- c_u: unit cost, x_t: units purchased/produced

4.2 Holding cost

If average on-hand inventory is I_t:

$$C_{hold} = \sum_{t=1}^{T} h \, I_t$$

- h: holding cost per unit per period (capital, warehousing, insurance, obsolescence)

4.3 Transportation cost

If shipments $s_{i,j,t}$ move on arcs (i,j):

$$C_{trans} = \sum_{t=1}^{T} \sum_{(i,j)} c_{i,j,t} \, s_{i,j,t}$$

4.4 Stockout / service penalty cost (drives "service level vs cost" trade-off)

Let unmet demand be $u_t = \max(0, D_t - \text{available}_t)$:

$$C_{stockout} = \sum_{t=1}^{T} p \, u_t$$

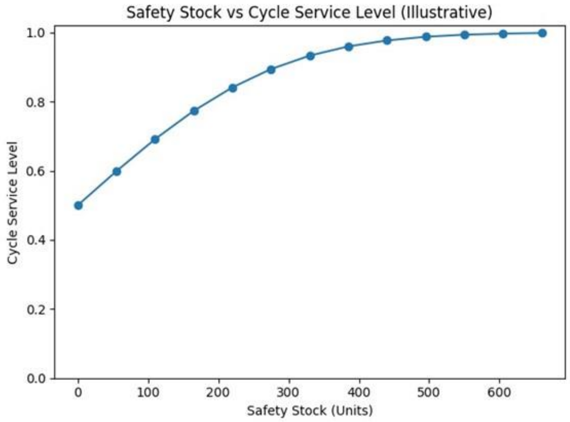
- p: penalty per unit short (lost margin, line stoppage risk)

This is the mathematical way to measure the paper's "stay close to TCO while improving service levels under volatility."

6. Case Studies and Empirical Evidence

The complexity of supply chain networks in automotive industries has significantly increased in the context of Industry 4.0. As highlighted in semiconductor supply chains, semiconductor products currently have long lead times. Moreover, the demand signal from the automotive sector is invisible, has high seasonality, has a multiproduct mix, and is highly uncertain. It is difficult for suppliers to fulfil the demand signals, such as quantity and product mix, on time. Due to these challenges, the role of automotive OEMs is changed. OEMs now take the leading role to drive and coordinate capacity and material supply in semiconductor supply chains. The mitigation strategies include sharing demand signals with suppliers to encourage early production and stockpiling before peak seasons, monitoring the dynamics of suppliers' supply capabilities and sign contracts for the predicted product mix and quantity with early lead time. The supply chain is also designed with more investments from automotive OEMs to secure necessary capacity and capability at selected first-tier suppliers. The developments of battery supply chains of electric vehicles are another important focus area. The requirements for battery supply chains comprise safety, cross-border movement, support of circular economy and green supply chains, and diversification of battery suppliers.

Electric-vehicle (EV) batteries and their components are needed for the manufacturing of electrical vehicles (EVs). Battery supply chains encompass many components and materials. Very few battery supply chains are operating now. Many countries aim to build battery supply chains in the coming years. These requirements have made the management of logistics for battery supply chains so complex. The logistics of battery supply chains have a strong focus on the circular economy. Containing order fulfilment lead times with reduced total costs are important. For electrical vehicle (EV) batteries, the testing time is very long. Therefore, sufficient testing capability needs to be prepared in advance, but the choice of testing capacity is often sub-optimal owing to uncertain demand signals. But there is insufficient capability in many testing centers. Due to safety reasons, some countries impose a ban on cross-border transport of batteries. Nevertheless, cross-border transport is still unavoidable in some cases. The volume of spent batteries that need to be recycled and treated is rapidly increasing. A Circular Economy is wanted because of its potential reduction in supply risk and lowering costs. Yet, when waste batteries are recycled, managing product return is still complex.



6.1. Automotive Semiconductor Supply Chains

Demand for automotive semiconductors is growing exponentially, driven by the increased electronic content of vehicles and demand for innovative functionalities, such as automated driving, connectivity, electrification, and even enhanced human–machine interfaces. Actual capacity, however, is far below requirements, with suppliers striving to maximize production of existing products under COVID-19 restrictions and fire damage at a key fabrication facility.

These elements all conspire to widen the demand–supply gap, resulting in extended lead times for certain products of one year or more. Far from resolving these challenges, the pandemic has been a wake-up call for the whole semiconductor industry. Supply chains have revealed all their vulnerabilities, with a lack of control over demand signals, insufficient visibility over the different stages of the cycle, and even a lack of supply-chain governance. OEMs controlling only 2 percent of the total industry value are now pushing for more influence and must urgently find the right balance between product mix optimization and recovery of service levels, while dealing with lead times translated into recovery time and revenue loss.

In this context, demand signals emerging from the automotive ecosystem need to be properly analyzed and reconciled with lead-time patterns, recovery times, product availability promises, and investment planning by semiconductor stakeholders. The latter can then design a prioritized action plan enabling strengthened supply–demand match in the short term, dedicated to lead-time reduction and risk mitigation. An AI-based visual tool embeds the analytical framework, validates the actual demand signals driving the automotive semiconductor supply chain, and enables industry players to define operational tactics and strategies for recovery. Performance quantification demonstrates the value of properly addressing these elements, with action on three fronts—balancing product mix across a consortium of OEMs, adopting demand management through allocation mechanisms, and restarting dormant capacity—culminating in reduced recovery times.

Equation 5: Transportation + network optimization (constraint-based formulation)

A standard **min-cost flow with capacity** formulation:

Decision variable

- $x_{i,j,t} \ge 0$: quantity shipped from node i to j in period t

Objective (cost minimization)

$$\min \sum_{t} \sum_{(i,j)} c_{i,j,t}\ x_{i,j,t}$$

Constraints

(1) Flow conservation (supply/demand balance)
For each node k and period t:

$$\sum_{i} x_{i,k,t} - \sum_{j} x_{k,j,t} = b_{k,t}$$

- $b_{k,t} > 0$: net demand at k; $b_{k,t} < 0$: net supply

(2) Capacity

$$0 \le x_{i,j,t} \le Cap_{i,j,t}$$

(3) Lead-time / delivery timing
If arc (i,j) has lead time $\ell_{i,j}$, then arrivals depend on earlier departures:

$$\text{Arrive}_{j,t} \supseteq x_{i,j,t-\ell_{i,j}}$$

Multi-objective extension (risk hedge)

Add risk term (e.g., disruption probability $r_{i,j}$):

$$\min\ \alpha \sum c_{i,j,t} x_{i,j,t}\ +\ (1-\alpha) \sum r_{i,j} x_{i,j,t}$$

This corresponds to the paper's "cost minimization with risk hedge against disruptions."

6.2. Electrical Vehicle Battery and Component Logistics

A case study on logistics for electric vehicle batteries and related components illustrates the application of predictive logistics for a rapidly evolving automotive supply chain. The analysis highlights the interdependencies of stock levels and performance outcomes across four geographies, two battery manufacturers, eight battery suppliers, a logistics service provider, and an automotive OEM. The emerging driving forces behind electrical vehicle adoption, such as increased safety and circularity requirements, alongside increasing lead times due to sourcing diversification, are found to enhance the performance benefits afforded by predictive logistics. The ECM approach is shown to enable improved service levels, lead times, and total cost of ownership for a predefined level of forecast accuracy and to support scenario analyses for both risk mitigation and opportunity exploitation.

Predictive logistics proved valuable to the automotive semiconductor supply chain by addressing demand forecast errors. Demand signals from neighboring geographical regions indicated an upsurge, while forecasts suggested stagnation. For electric vehicles, parallel supply chains are winding up for battery and battery-component manufacture, with dramatic customer safety concerns and regulatory requirements on heavy metals and circularity. These elements are pooling customer behavior towards early supply chain requirements, forcing automotive OEMs to tap on dual supply scenarios with two or more battery suppliers and/or a change of supply route with added lead times. Stock levels at the battery OEM and its suppliers now gravitate towards fulfilment of market requirements and safety aspects.

7. Conclusion

Predictive logistics heightens the presence and integration of collaborative decision support tools for supply chain and logistics managers. Forecasting offers the best Lead Time, yet may have the lowest accuracy. Prescriptive optimization maximizes performance against given demand estimates. Real-Time Decision Support yields improved Service Levels in the presence of volatile Demand and possible Transport disruptions while remaining close to the Total Cost of Ownership of the Prescriptive plans.

AI-DRIVEN PREDICTIVE LOGISTICS FOR DISTRIBUTED AUTOMOTIVE SUPPLY NETWORKS UNDER INDUSTRY 4.0 CONSTRAINTS advances understanding of the industrial context, drivers, gaps, and best-practice development process; assembles performance metrics; and supervises predictive logistics implementations to achieve optimized AI-driven predictive logistics across

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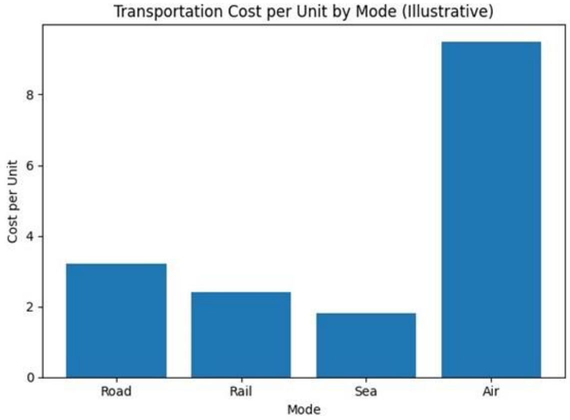
distributed automotive supply networks, while under the constraints of Industry 4.0. Decision-support performance is evaluated against Accuracy, Lead Time, Service Level, and Total Cost of Ownership, and evidence is presented for two distinct applications associated with the supply and transport of electric vehicle semiconductor components.



7.1. Future Trends

Societal, technological, and regulatory megatrends are prompting next-generation automotive supply chains that are environment- and customer-centric, user-friendly, resource-efficient, and resilient. Advanced sensors for real-time data capture on manufacturing processes and product performance will enhance visibility and enable real-time simulations of vehicle operation and use. AI models that digitally reflect the behaviour of fleet customers, suppliers, and logistics operations will drive supply strategies and logistics executions. Emerging platform ecosystems will enable data sharing and collaborative decision support among supply chain partners and even with competitors. Government policies will facilitate programme funding, semiconductors and other resources, renewable energy infrastructure, and testing facilities for next-generation automotive electronics.

Evidence on predictive logistics for supply networks under Industry 4.0 constraints is still limited. Critical building blocks include suitable data governance frameworks; privacy-preserving techniques for utilising sensitive data; edge computing to enable local intelligence in connected resources; and Industry 4.0 maturity models for assessing readiness levels of individual partners and entire networks. Different types of automotive supply chains can have fundamentally different requirements for sourcing safety-related components, satisfying end-user circularity needs, or minimising the total cost of ownership. These differences need to be understood, especially when forecasts indicate that supply constraints may last several years.

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