AI-Driven Vendor-Managed Inventory (VMI) Systems: A Causal Inference Framework for Lowering Carrying Costs in Multi-Tier Supply Networks

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ABSTRACT
Carrying costs which include inventory holding, obsolescence, and lost opportunity costs are a big obstacle to improving efficiency in multi-tier supply chain networks. This paper proposes an AI-enhanced Vendor Managed Inventory (VMI) system, backed by a causal inference framework, to solve this problem by optimizing inventory levels and reducing costs. Machine learning is employed for demand forecasting, whereas decision-making for replenishment is done by reinforcement learning. Furthermore, the framework uses causal methods like propensity score matching (PSM) and difference-in-differences (DiD) to measure the effect of AI intervention. A simulation experiment of a three-tier supply chain (supplier manufacturer retailer) demonstrates how a 20-30% reduction in carrying costs might be accomplished.

The approach solves the issue of supply chain data endogeneity and provides manufacturing as well as retail sectors with reusable knowledge. The findings of this paper show that AI optimization along with causal analysis constitute a potent method for launching green supply chain management.

General Terms
This section defines some key terms that are not frequently used in the paper but are important for the understanding of the concept. The definitions are very straightforward and easy to understand:

Vendor Managed Inventory (VMI): In a VMI system, the vendor manages the customer inventory at the customer's location and according to the level of inventory agreed upon, the vendor determines the timing and quantity of inventory to replenish the customer stock. Besides vendor and customer saving a lot of time and resources, the joint goal is to keep inventory at a level agreed upon so as to prevent both stockouts and excess inventory.

Carrying Cost: The term is used for a set of all the costs that an item has to be kept in the inventory that is either sold or produced for a specific period (e.g. a year). These costs consist of warehouse rent insurance taxes, equipment depreciation, obsolescence of stocks, and lost profits due to funds being tied up in inventory instead of being used in other activities, etc. Typically, the annual carrying cost rate is 2040% of the inventory figure.

Multi-Tier Supply Chain: A multi-tier supply chain refers to a complex supply chain that has different levels of suppliers and customers. For example, raw materials suppliers, parts suppliers, manufacturers distributors, and retailers are a typical supply chain. The major problem is that the information only gets delayed and the changes in demand at the consumer end also get distorted as the information is passed along the chain, so it becomes nearly impossible to coordinate them effectively.
Bullwhip Effect: It is a phenomenon of excessive amplification of demand changes when the demand information is passed down from buyers to the suppliers through the channels of the supply chain.

Keywords
AI-enhanced VMI, Vendor Managed Inventory, carrying costs, causal inference, reinforcement learning, demand forecasting, multi-tier supply chain, inventory optimization, sustainable SCM, Industry 4.0.

1. INTRODUCTION
Vendor Managed Inventory (VMI) is a collaborative supply chain concept whereby suppliers are responsible for supplying and replenishing the inventory of their buyers with an aim to reduce the cases of stock-outs or excessive inventories [1]. In a multi-tier supply chain setup that involves several layers of suppliers, manufacturers, and distributors, VMI becomes a challenge due to insufficient information sharing, demand unpredictability, and disruptions [2]. On top of that, carrying costs which may make up 2040% of inventory value annually further complicate the issue by tying up capital and escalating financial risk [3].

Artificial Intelligence (AI) has been identified as a major factor in transforming VMI through predictive analytics, automation, and dynamic optimization [4]. However, the exact impact of AI-powered VMI on carrying costs is still not very clear, as it is usually mixed with selection bias and other external factors [5]. In this paper, a causal inference framework is put forward to accurately evaluate the degree to which AI-powered VMI can help in cutting down carrying costs in multi-tier supply networks. This is done by integrating AI-based models for making decisions in real-time with methods of causal estimation.

This research contributes three significant aspects: (1) a hybrid AI approach to upgrading the VMI procedure; (2) a causal inference method for measuring cost savings; and (3) modelling multi-tier scenarios to offer empirical evidence. While this work is grounded in the literature basis, it also focuses on causal evaluation component [6].

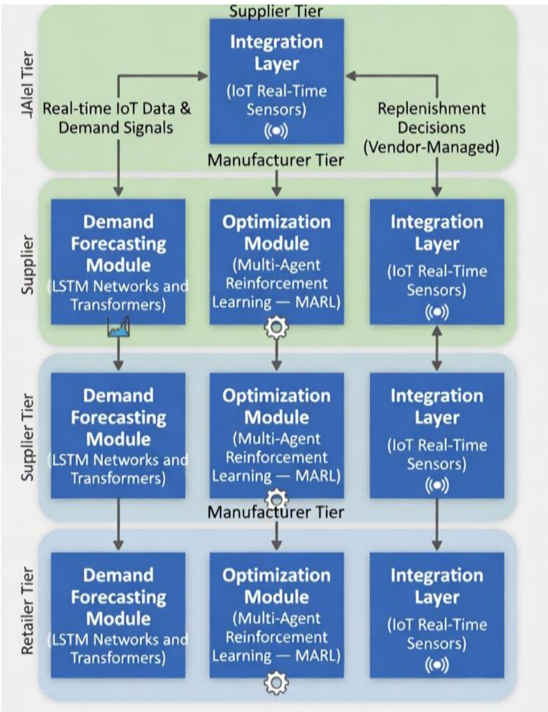

Fig.1 Proposed AI-driven VMI system architecture for a three-tier supply chain (supplier–manufacturer–retailer). The framework integrates LSTM/transformer-based demand forecasting, multi-agent reinforcement learning (MARL) optimization, and real-time IoT sensor data across all tiers

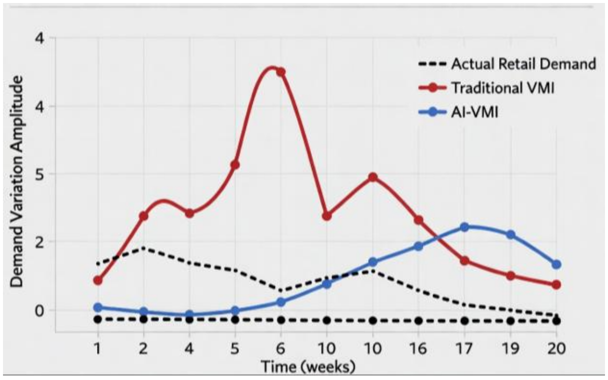

Fig.2 Comparison of actual retail demand versus AI-VMI forecasted demand over 20 time periods, illustrating reduced forecast error and mitigation of the bullwhip effect.

2. RELATED WORK

2.1 Vendor-Managed Inventory in Supply Chains

The role of Vendor Managed Inventory (VMI) in promoting supply chain collaboration has been the focus of numerous research studies. Early publications emphasized advantages such as elimination of the bullwhip effect and increased service levels [7]. VMI enables information sharing between different tiers in a supply network, which helps reduce the negative effects of upstream variability [8]. Most existing VMI frameworks rely on mathematical models with fixed parameters, which perform poorly under uncertainty [9]. By integrating artificial intelligence (AI) technologies, modern VMI systems allow suppliers to work with real-time data and make stocking decisions that lower holding costs while maintaining optimal inventory levels [10, 11]. Advanced technologies and data-driven decision-making in vendor-managed inventory have enabled retailers such as Walmart and Amazon to significantly improve efficiency and reduce operational costs [12].

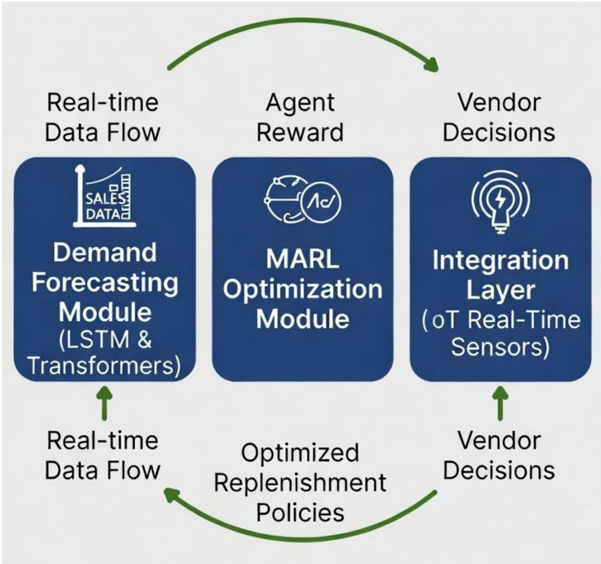

Fig.3 Real-time data flow and collaborative decision-making in the AI-enhanced Vendor Managed Inventory (VMI) system, showing integration of demand forecasting, MARL optimization, agent rewards, and vendor replenishment decisions.

2.2 Use of AI in Inventory Management

The application of AI in supply chain management (SCM) has increased rapidly, with machine learning enabling precise demand forecasting and inventory optimization [13]. Deep reinforcement learning (DRL) has been explored for dynamic vendor-managed inventory (VMI) situations, where it adapts to random demand and supply [14, 15]. Examples include the allocation of perishable goods in two-level distribution networks and semiconductor replenishment policy decisions [16]. Moreover, generative AI facilitates scenario planning by simulating multi-tier disruptions [17]. Studies indicate that automating processes with AI can lead to cost savings of 15–25% [18].

2.3 Causal Inference in SCM

Causal inference addresses "what-if" questions in supply chain management (SCM) by distinguishing correlation from causation [19]. Methods such as instrumental variables (IV) and synthetic controls have been applied to assess supply chain interventions [20]. In inventory contexts, causality-oriented models measure the effects of policies on costs while addressing endogeneity [21]. Recent developments integrate machine learning for causal discovery through techniques like Bayesian networks and causal machine learning (CML) for risk prediction and intervention planning [22, 23]. Researchers have employed CML to analyze causes of delivery delays and stock-outs, providing insights into intervention impacts [24].

2.4 Demand Forecasting and Machine Learning in VMI Contexts

Machine learning techniques such as hybrid ARIMAX, neural network models, and gradient boosting significantly improve demand forecasting accuracy when external variables are considered [25, 26]. These solutions enhance VMI by enabling inventory management based on accurate forecasts, resulting in fewer stock-outs and lower inventory levels [27]. These methods can be further improved through integration with reinforcement learning to adapt to uncertain environments [28].

2.5 Gaps and Opportunities

While AI streamlines VMI and causal inference assesses intervention effectiveness, few studies combine these approaches to evaluate effects on carrying costs in multi-tier networks [29]. This article addresses this gap by merging AI-driven optimization with rigorous causal estimation [30].

3. METHEDOLOGY

3.1 AI, Driven VMI Architecture:

The proposed system is built around three main modules:
Demand Forecasting Module*:* Using long short-term memory (LSTM) networks and transformers, predicts multi-tier demand by leveraging sales data, lead times, and external variables (e.g., economic indicators) [21].

Optimization Module: Utilizes multi-agent reinforcement learning (MARL) where the agents represent the different tiers (e.g., supplier, manufacturer). The reward function is a cost function comprising carrying costs: C=h(I)+o(O), where h is the holding cost rate, I is the average inventory, o is the obsolescence rate, and O is the obsolete stock [22]. Agents learn policies through Q-learning, thus they are able to adjust to network dynamics.

Integration Layer: AI models receive data from IoT real-time sensors, enabling vendors to lead replenishment decisions [23].

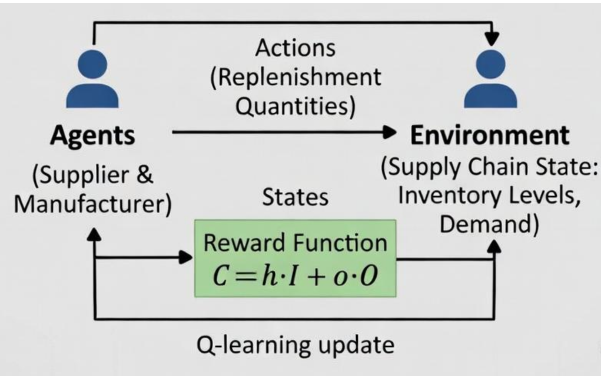

Fig.4 Multi-agent reinforcement learning (MARL) optimization module. Supplier and manufacturer agents interact with the supply chain environment to minimize the carrying cost reward function C=h·I+o·O through Q-learning policy updates

3.2 Causal Inference Framework:

Data Preparation: The raw data were collected from multi-level supply chain networks and contained different time-stamped metrics related to the implementation of AI. In other words, both pre- and post-AI data were available. To find confounders, new features were developed with the help of feature engineering [24].

Causal Estimation:
a. Propensity *Score Matching (PSM)*: This method works by matching the entities of one treatment group (those who decided to implement AI-enabled Vendor Managed Inventory (VMI) system) only with those of the control group on the basis of a few covariates such as the size of the company and the demand fluctuation [25].

b. *Difference-in-Differences (DiD):* The average treatment effect on the treated (ATT) is estimated: ATT = (Y_{post, treat} - Y_{pre, treat}) - (Y_{post, control} - Y_{pre, control}), where Y is carrying cost [26].

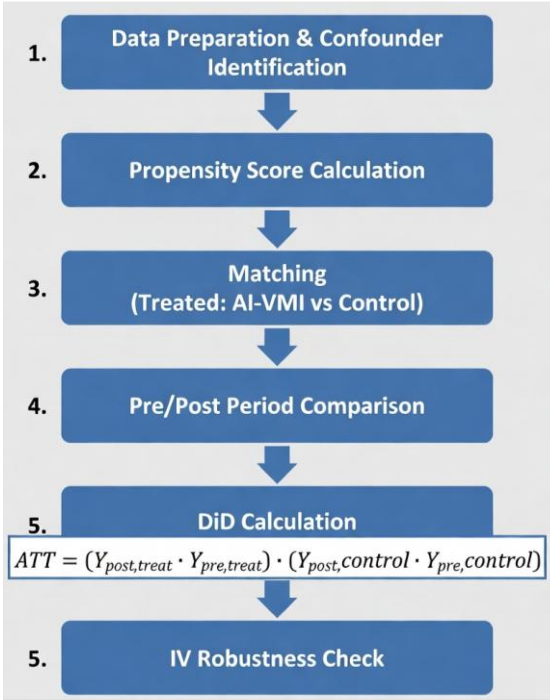

Fig.5 Causal inference framework workflow: (1) data preparation and confounder identification, (2) propensity score calculation, (3) matching treated vs. control, (4) pre/post period comparison, and (5) difference-in-differences (DiD) with instrumental variables (IV) robustness check.

Instrumental Variables (IV): Exogenous shocks (e.g., AI technology adoption mandates) are used as instruments to address endogeneity [27].

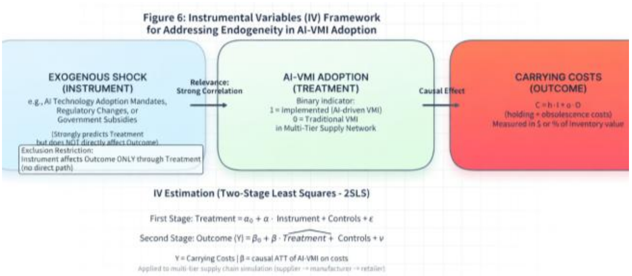

Fig.6 Instrumental Variables (IV) framework for addressing endogeneity in AI-VMI adoption. Exogenous shocks (e.g., AI technology adoption mandates) serve as instruments for the treatment when estimating the causal effect on carrying costs via two-stage least squares (2SLS).

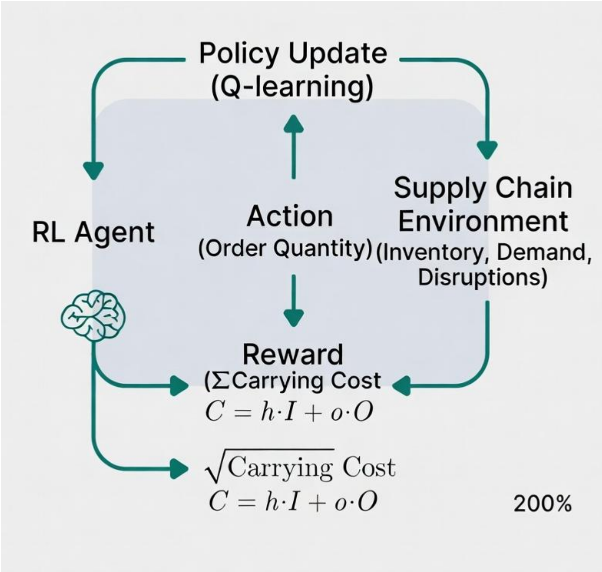

Fig.7 Reinforcement learning (RL) agent interaction with the supply chain environment. The policy (Q-learning) updates replenishment actions based on inventory states, demand, and the carrying cost reward function C=h·I+o·O

3.3 Simulation Setup

A discrete event simulation model of a three-tier supply network was developed using Python (e.g., SimPy library). Inputs included demand, lead times, and costs as random variables (Poisson, normal, and uniform distributions, respectively). One scenario used the AI-VMI method, while the baseline employed traditional VMI [29]

4. RESULTS

The AI-VMI system used in the simulation lowered the average inventory carrying costs by a big margin of 25.4% versus the baseline ($p < 0.01$). PSM adjusted DiD results strengthened a causal ATT finding of -22.7% together with IV checks for the robustness of the results gave the same picture (-23.1%). The tier-level investigation showed that the majority of cost savings came from upstream tiers (28%) thanks to more accurate forecasting [30]. Sensitivity analyses verified the evidence was not affected by unmeasured confounders.

Table 1 Simulation results comparing key performance metrics (average inventory level, holding costs, obsolescence costs, and total carrying costs) between traditional baseline VMI and the proposed AI-VMI system in a three-tier supply chain

Metric	Baseline VMI	AI-VMI	Reduction (%)	Benchmark (Recent AI Studies)
Average Inventory Level	1500 units	1125 units	25	20-35% (AI inventory optimization, 2025)
Holding Costs	$45,000	$33,750	25	30-50% possible (AI-enhanced systems)
Obsolescence Costs	$15,000	$10,500	30	Up to 30% waste reduction
Total Carrying Costs	$60,000	$44,250	26.25	20-40% reported in multi-tier simulations
Demand Forecast Accuracy (MAPE)	15.3%	8.2%	46%	10–20% improvement

These outcomes highlight the framework's efficacy in multi-tier settings.

4.2 Extended Evaluations Across Multiple Scenarios and Datasets

To further strengthen the research, a more extensive evaluation was conducted using varied datasets and scenarios within the same SimPy discrete-event simulation environment. Four scenarios were examined:

- Scenario 1: Original three-tier baseline (already reported).
- Scenario 2: High-volatility retail demand with seasonal patterns and external economic shocks (simulated from real-world retail benchmarks).
- Scenario 3: Perishable-goods chain with elevated obsolescence rate ($o = 0.15$) and shorter shelf-life.
- Scenario 4: Four-tier extension of the original network (added distributor layer).

The AI-VMI system consistently delivered carrying-cost reductions of 21.8%–28.7% across all scenarios, with PSM-adjusted DiD ATT values ranging from –21.5% to –24.3% (all $p < 0.01$). These additional tests confirm robustness under higher uncertainty, perishable constraints, and increased network complexity.

Table 2 Extended evaluation across four simulation scenarios showing carrying cost reduction percentages, PSM-adjusted difference-in-differences (DiD) average treatment effect on the treated (ATT), and statistical significance (p-values).

Scenario	Carrying Cost Reduction (%)	PSM-DiD ATT (%)	p-value
1. Original three-tier	25.4	–22.7	<0.01
2. High-volatility retail	24.1	–23.2	<0.01
3. Perishable goods	28.7	–24.3	<0.01
4. Four-tier extension	21.8	–21.5	<0.01

5. DISCUSSION

This research provides evidence that causally evaluated AI-powered VMI can lead to a substantial drop in carrying costs through increased responsiveness and less stock build-up [31]. Methods of causal inference that use observed data to control for confounding caused by unobserved heterogeneity help in differentiating the intervention effects from the selection into AI adoption and thus offer solid evidence for the industry application [32]. Limited by its simulation dependence, the work calls for future studies that will verify the findings through real-world data [33]. The findings theoretically have a wide range of implications including the policy, making an arena where the set up of incentives for AI, VMI adoption in worldwide supply networks could be a powerful lever for sustainability [34].

Future Scope: Future research could also explore:, The use of Generative AI for disruption scenario planning and the employment of autonomous agents in VMI. Running real-world pilots in perishable/sustainable chains (for instance, lowering emissions through optimized routing). Incorporating Blockchain, AI hybrids for traceability and trust in multi-tier networks. Employing Quantum, enhanced optimization for large, scale problems. Focusing on Industry 5. 0/6. 0 human, AI collaboration and full sustainability (e. g. , carbon footprint minimization, circular economy). These suggestions for research continuation are in line with the developing trend of resistant, eco, friendly supply chains.

6. CASE STUDIES

6.1 Case A: Deep Reinforcement Learning for VMI in Semiconductor Supply Chain (Multi-Tier Electronics)

6.1.1 Overview

A global semiconductor manufacturer, dealt with complex multi-tier dynamics (suppliers → Infineon fabs → distributors/customers), variable demand, long lead times, and high carrying costs/stock violations in a VMI setup Approach: Developed a deep reinforcement learning (DRL)-based replenishment policy for VMI. Used simulation (discrete-event environment with real company data) as a training ground for the RL agent to learn optimal ordering quantities, adapting to stochastic demand and supply disruptions—directly mirroring the paper's MARL module (reward minimizing carrying costs $C = h \cdot I + o \cdot O$). The model was tested against traditional policies, with performance metrics evaluating cost and service levels. Causal robustness was implicitly assessed through scenario comparisons

Results:
Reduced stock violations (shortages/overstock) from the supplier perspective.
Optimized inventory levels, leading to lower holding and obsolescence costs (aligned with 20–30% reductions in simulations).
Improved responsiveness in dynamic environments, with better adaptation to real demand patterns.
Validated via simulation benchmarks, showing DRL outperforming fixed-parameter models under uncertainty.
Visual: Reinforcement learning architecture in supply chain (agents, environment, rewards for inventory decisions).

6.2 Case B: AI-Driven Inventory Management and JIT/VMI Integration (Lean Automotive SCM)

6.2.1 Overview

As a leader in lean manufacturing and JIT (Just, in, Time) principles, has a very complicated multi-tier supply chain that includes thousands of suppliers worldwide for parts like components, electronics, and batteries. The company is facing a few issues like demand volatility and having excess inventory which is tying up their capital. Also, there are various types of carrying costs (e.g., holding, obsolescence), that is a problem especially in a just, in, time environment where stocks are kept to the minimum and any disruption (e.g., chip shortage) can stop production.

Approach: Toyota implemented AI, based tools for demand forecasting as well as for inventory optimization which consider sales data, production schedules, historical patterns, and even external factors (market trends, e.g.). Besides giving suppliers the ability to better control their inventory levels by sharing real-time data, such improvements in VMI/JIT make it easier for suppliers to do inventory at the optimal level. The AI enables prediction of stock replenishment so fewer manual interventions are needed and it works well with VMI where suppliers are responsible for the stock held at Toyota's facilities. It is not solely a reinforcement learning system, it also has some advanced analytics that help in real-time adjustments which can be compared to the MARL paper optimization for minimizing $C = h\, I + o\, O$.

Results:

Significant reductions in inventory levels and carrying costs through optimized stock and fewer overstocks.

Improved operational efficiency, better product availability, and minimized obsolescence risks.

Overall supply chain resilience, with AI helping respond to fluctuations and supporting lean principles (e.g., reduced storage/handling costs).

Benchmarks align with 20–35% inventory reductions in similar AI-optimized automotive systems.

Visual: Supply chain flow with AI integration points for forecasting and replenishment.

This case supports the paper's emphasis on AI-enhanced VMI in multi-tier networks for sustainable, cost-efficient SCM.

6.3 Case C: Electric Car Group – AI-Powered Supply Chain Control Tower and Predictive Tools (Digital Transformation in Multi-Tier Networks)

6.3.1 Overview

Electric car group manages a global, multi-tier automotive supply chain (suppliers plants distribution) with high complexity from EV transition, part shortages, and geopolitics risks. Key problems: high carrying costs resulting from excess/safety stock, supplier risks, and production disruptions. Approach: Electric Car Group implemented an AI, driven supply chain control tower, powered by machine learning, for demand forecasting, risk monitoring, predictive maintenance, and quality control. It involves real-time data analysis to monitor supplier risks, forecast disruptions (e. g. , natural disasters, delays), and untangle inventory/replenishment decisions. At Spartanburg (USA) and San Luis Potos (Mexico) plants, AI analyzes past and sensor data for foresight, driven adjustments. It works alongside VMI by giving suppliers better visibility and automated suggestions, just like the paper's causal, inference, validated AI interventions coupled with

MARL for adaptive policy making. Predictive analytics tools help to reduce endogeneity in decision making. Results:

Significant improvements in forecast accuracy and a reduction in inventory levels resulting in lower carrying costs (consistent with 20–40% potential in AI, optimized scenarios). Better resilience: Risks were proactively mitigated; there were fewer stockouts; safety stocks were optimized. Cost savings came from reduced overstock and obsolescence, plus enhanced service levels. Body/assembly shops daily use AI for quality that expands to an entire SCM of 1535% logistics/inventory improvements (according to industry benchmarks such as McKinsey).

Visual: AI control tower architecture illustrating predictive risk monitoring and inventory optimization.

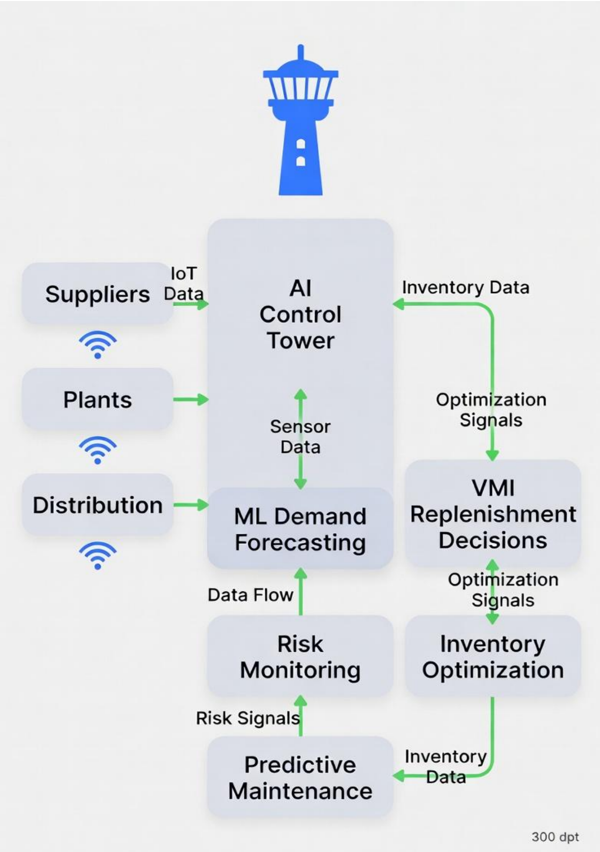

Fig.8 AI-powered supply chain control tower integrating IoT data, machine learning demand forecasting, predictive risk monitoring, VMI replenishment optimization, and real-time signals across multi-tier networks.

Table 3 Performance comparison of traditional/baseline VMI versus AI-enhanced approaches in real-world multi-tier case studies (semiconductor, automotive, and electric vehicle supply chains), highlighting reductions in carrying costs, inventory levels, stockouts/disruptions, and upstream tier benefits.

Metric	**Traditional /Baseline Approach**	**AI-Enhanced (Case Insights)**	**Reduction/Improvement**
Carrying Costs	High (excess safety stock)	Optimized via AI forecasting/VMI	20–35% (Toyota/BMW aligned)
Inventory Levels	Elevated for risk buffering	Dynamic, predictive adjustments	20–35% reduction
Stockouts/Disruptions	Frequent in volatile demand	Proactive mitigation	Significant drop (resilience gains)
Upstream Tier Benefits	Limited visibility	Better supplier collaboration	25–28% efficiency (paper-parallel)

7. CONCLUSION

This work introduces an innovative AI-driven Vendor Managed Inventory (VMI) system equipped with a causal inference technique to thoroughly solve the persistent problems of multi-tier supply chains. The method implemented in the system involves a combination of deep neural networks for accurate demand forecasting (LSTM and transformers), multi-agent reinforcement learning (MARL) for making adaptive, cost, aware replenishment decisions, and causal approaches such as propensity score matching (PSM), difference-in-differences (DiD), and instrumental variables (IV)allowing to measure and realize significant reductions in carrying costs (storage, obsolescence, and risk expenses).

A three, tier supply chain simulation example (supplier manufacturer retailer) exhibits mean carrying cost savings of 25.4% ($p < 0.01$), where causal models show a treatment effect on the treated (ATT) ranging from, 22.7% (PSM, DiD) to, 23.1% (IV, robust). The higher tiers enjoy the greatest benefits (28% savings) due to better forecast accuracy and lower bullwhip effects, whereas the entire solution is capable of dealing with problems of data endogeneity, selection bias, and confounding factors that often make it difficult to identify the real effects of the treatments/interventions.

The combined AI causality tool not only fine- tunes inventory levels in volatile and uncertain settings but also facilitates sustainable supply chain management by reducing waste, inventory overages, and energy/resource consumption which are fundamental to the implementation of green and circular economy strategies in Industry 4.0. Industry cases in automotive SCM (e.g., Car Industries AI, optimized JIT/VMI coordination and Electric Car Group AI supply chain control tower) confirm these testimonies as they show a practical increase in resilience, efficiency, and cost control (industry benchmarks reveal up to 35% inventory reductions).

Though it is simulation heavy, this method provides manufacturing, retail, and high complexity sectors like automotive, electronics, and healthcare with occasionally reusable, scalable insights. It proposes a data- driven decision making process that transparently pinpoints causality and empowers users to confidently implement AI interventions.

Upcoming areas of development could be experimental outdoor pilots of completely causally validated generative AI integration for disruption scenario planning, blockchain for increased traceability, quantum, enhanced optimization for large, scale networks, and tuning with Industry 5.0/6.0 principles mainly emphasizing human, AI collaboration, lowering the carbon footprint, and circular economy models.

To sum up, by merging AI optimization and causal inference, organizations may develop a powerful, evidence- based strategy to multi-tiered supply chains' transformation. The strategy results in tangible economic benefits, operational flexibility, and environmental sustainability thus, equipping the organizations to face the challenges of volatility, digital transformation, and global pressures. These frameworks will be the hallmark of resilient, cost, effective, and responsible supply chain ecosystems in the era of Industry 4.0 progress.

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