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Article

Supply chain network based on Block Chain and deep learning

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Abstract: Recent studies have explored blockchain technology and Graph Neural Networks (GNNs) in supply chain management; however, most approaches focus on isolated tasks such as demand forecasting or supplier evaluation without integrating intelligent decision-making and secure transaction verification within a unified framework. This paper proposes an intelligent supply chain management framework that combines Graph Neural Networks (GNNs), Multi-Agent Systems (MAS), and blockchain technology to improve prediction accuracy, operational transparency, and decision reliability. The proposed model represents suppliers, warehouses, inventory units, and logistics routes as interconnected graph structures to capture complex relational dependencies. Intelligent agents support inventory forecasting, supplier evaluation, and logistics planning, while blockchain technology ensures secure and tamper-resistant transaction recording. Experimental results using a real-world supply chain dataset demonstrate that the proposed framework achieves approximately 97% prediction accuracy with low error rates (MSE = 0.003 and RMSE = 0.02), outperforming several recent supply chain prediction models. The findings confirm the effectiveness of integrating GNN-based learning with blockchain-enabled verification for intelligent and scalable supply chain management.
Keywords: Supply chain network, block chain, deep learning, Intelligent agent, graph neural network

1. Introduction:

The global business landscape is undergoing a paradigm shift toward a digital economy, characterized by the principle of hyper-connectivity. This phenomenon represents the intensified integration of individuals, organizations, and industrial assets, facilitated by advanced mobile networks and Internet of Things (IoT) devices. The pervasive digitization of commerce has catalyzed the emergence of intelligent digital networks, fundamentally transforming how resources are managed, optimized, and deployed. Within this increasingly customer-centric marketplace, supply chain management (SCM) has evolved from a back-end operational function into a primary determinant of competitive advantage [1] . In the contemporary global economy, the widespread availability of mobile internet and social networking has disrupted traditional business models. This paradigm shift presents a multifaceted range of opportunities and challenges for organizations, particularly within the supply chain management (SCM) domain. Given the unprecedented proliferation of Big Data, advanced data analytics has become essential for synthesizing vast datasets into actionable intelligence. This transition from raw data to meaningful information is now a critical driver of operational efficiency and strategic agility in modern supply chains[2]. Blockchain technology functions as a decentralized, distributed ledger that records transactions immutably within a series of interconnected blocks. Each block incorporates a cryptographic hash of the preceding block, establishing a sequential chain that ensures data integrity and protects against unauthorized tampering. This structural dependency creates a cascading validation effect: any modification to a single block invalidates the hash of all subsequent blocks, thereby immediately exposing the attempted alteration and ensuring the reliability of the entire ledger[3].Various blockchain platforms provide robust frameworks for developing decentralized applications (DApps) tailored to specific industrial requirements, ensuring


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both operational efficiency and systemic reliability. These platforms are particularly effective in the context of the supply chain, which functions as a dynamic network of interconnected processes and activities designed to generate value for the end consumer.By facilitating upstream and downstream linkages, the supply chain coordinates a continuous flow of information, physical goods, and financial capital across its various stages. Structurally, the modern supply chain resembles a complex network topology—or a multidimensional web—where stakeholders act as nodes interconnected through intricate dependencies across the entire lifecycle of a product[4].Blockchain technology reduces transaction costs in a circular model by improving performance and communication along the supply chain, as previously highlighted[5].Blocks within a blockchain are interconnected and synchronized through advanced cryptographic mechanisms. Each constituent block encapsulates an encrypted hash of the preceding block, a precise temporal timestamp, and comprehensive transaction-related data. This linked architecture confers structural integrity upon the chain, rendering its contents tamper-resistant and ensuring the absolute reliability of transaction recording and multi-party verification.[6]Intelligent systems driven by machine learning (ML) are typically architected with advanced artificial intelligence capabilities. At its core, machine learning enables systems to iteratively learn from problem-specific training data, thereby automating the construction of complex analytical models to solve targeted tasks. Deep Learning (DL) represents a specialized paradigm of machine learning centered on multi-layered artificial neural networks. Due to their ability to automatically extract hierarchical features from raw data, deep learning models frequently demonstrate superior performance compared to shallow machine learning architectures and traditional statistical analysis approaches across a wide range of industrial applications[7],[8].

The main contribution of this research is to develop an integrated intelligent framework for supply chain management by integrating Graph Neural Networks GNNs, Multi Agent Systems MAS, and blockchain technologies within a unified architecture capable of addressing dynamic complexity in modern supply chain networks. Unlike traditional deep learning models that treat supply chain data as independent records, the proposed system relies on representing supply chain components as an interconnected graph architecture in order to capture spatial relationships The complex structural interconnections between suppliers, warehouses, storage units, and transportation routes. The research also presents a mechanism based on intelligent agents to support decentralized decision-making in inventory processing, supplier evaluation, and logistics optimization processes. In addition, blockchain technologies are integrated to provide a reliable and transparent environment based on tamper-evident verification of transactions and operational data within the network. Dynamic operational factors such as traffic conditions, weather factors, and supplier reliability are also included To more accurately represent real-world supply chain environments, experimental results showed that the proposed model achieved an accuracy of approximately 97% with low values for both MSE and RMSE, outperforming a number of state-of-the-art models used in supply chain management applications. This confirms the model's efficiency in improving prediction accuracy, operational decision reliability, and scalability within intelligent supply chain environments

1.2 Related work

In practice, many applications of blockchain technology, artificial intelligence, multi-agent systems, and neural network models have been reported in the scientific literature to develop and improve the efficiency of supply chain management practices. Recent studies have also introduced various solutions to help increase supply chain performance in terms of transparency, security, predictive accuracy, and decision support. Among these, the most apparent is that each involves solving an engineering problem, and all of them are directly proportional to the issues that may be faced. Zahraa Al Sahili and Mariette Awad in 2023 [9]. The potential of graph neural networks, which have attracted greater attention in recent years because of their ability to generalize deep learning models to data distributed across non-Euclidean spaces, may be the focus. Nevertheless, most of these models rely on an invariant graph framework, which may hinder their performance when representing data moving over time. To remedy this problem, spatiotemporal graph neural networks were proposed as a new frontier of the model that embeds momentum into the learning. Give a glimpse of the evolving dynamics of relationships and network structures in the process to reflect more authenticity. The current survey provides an overview of this model and a methodical classification of spatiotemporal graph neural networks into two groups based on the mechanism that generates temporal variation. The

paper also details a wide variety of similar applications and concludes with an overview of prospective work based on challenges in this field today.

Peter Gonczol and Panagiota KatsikoulI and et al. in 2024 . Modern supply chains have become highly interconnected and dynamic systems in which multiple parties, such as suppliers, manufacturers, distributors, and retailers, interact continuously through changing time relationships. Although data analytics and machine learning technologies have advanced significantly, many current models still cannot accurately capture the complex relational dependencies within these networks. This is because traditional deep learning models treat supply chain data as separate, independent records, ignoring the network-based, graph-like nature that governs interactions and relationships among the system's components[10].

Desheng Wu and Quabbin Wangmines et al. in (2023). The purpose of proposing a methodology that leverages latent information extracted from the supply chain network is to classify participating companies. A dataset of supply chain networks for listed companies is constructed, and neural network algorithms are then employed to classify these companies more accurately. Experimental results show that this method is highly effective and outperforms traditional machine learning methods, achieving an average improvement of more than 2% in the accuracy of classifying industrial sectors of listed companies while significantly reducing classification time[11].

Edward Elson Kosasih and Alexandra Brintrup (2021)discuss the importance of gaining visibility into procurement interdependencies between suppliers to develop more informed business contingency plans. However, existing methods, such as supplier surveys, rely on suppliers' willingness or ability to share data and are not easily verifiable. In this article, we pose the supply chain visibility problem as a link prediction problem from the field of Machine Learning (ML) and propose the use of an automated method to detect potential links that are unknown to the buyer with Graph Neural Networks (GNN)[12].

In (2024)Amy Ancelotti and Claudia Liason use graph neural networks (GNN), graph convolutional networks (GCN), and convolutional neural networks (CNN) in blockchain applications to resolve the issues posed by the increasing complexity of decentralized systems, which makes classical techniques insufficient to decipher relationships and dynamic functions at the network level. Deep learning models solve this issue effectively by capitalizing on the network nature of both node and transaction data. In particular, GNNs and GCNs are especially good at representing the relations between nodes and transactions in order to better handle tasks like fraud detection, transaction verification, and smart contract analysis as per our research problems. On the other end, CNNs can be employed to visualize blockchain data into a matrix format in order to find temporal and spatial features of the way of transactions, as well when temporal or spatial pattern in the behavior for the flows of transactions are presented[13].

This GNN model is embedded in a smart agent which acts as a miner in the entire system. The agent uses the graph representations of events computed, validates them with their correctness, and retrieves meaningful data from its network. In summary, once an event is confirmed, the agent logs the verified transaction on a decentralized blockchain ledger for transparency, integrity and complete auditability along the supply chain.

2. Blockchain technology in the supply chain

Blockchain technology facilitates the sharing of transaction data through a decentralized and distributed digital ledger. Its inherent immutability makes it an ideal solution for enhancing transparency and systemic integrity [14]. Beyond supply chain management, blockchain is being extensively studied across diverse domains including real estate, government services, and intellectual property to mitigate fraud and improve operational ease of use. However, widespread adoption is currently constrained by significant challenges, most notably limited scalability, interoperability issues, and high energy consumption [15]. Despite these hurdles, the theoretical and practical potential for blockchain integration remains immense due to its ability to ensure traceability, authenticity,and transparency[16]. Recent systematic reviews emphasize that blockchain-enabled supply chain systems must be rigorously evaluated based on the depth of traceability, transparency levels, and their ability to cover multiple tiers of the network [17].

Furthermore, technical challenges persist regarding integration with legacy systems, flexible access control, and compliance with evolving data protection regulations [16], [18].

2.1 Deep learning

In the last few years, deep learning has transformed many of such machine learning tasks like image classification, video processing, speech recognition and natural language understanding. The most common way to represent data over the years has been in Euclidian space however, many modern applications produce data from non-Euclidean domains where information is presented in graphs with digits corresponding to complex relationships and multidimensional correlations making it difficult for traditional machine learning algorithms due to their inability of understanding the nonlinear structure within these networks.[19][20].

2.2 Graphical neural networks in supply chains

Graph Neural Networks are a specific type of deep learning model that is used to process data represented as graphs. They work by exchanging messages through an iterative message-passing framework where information is exchanged and aggregated between connected nodes in several layers to update their node and edge representations. Evidence from recent studies has pointed to a superiority of GNNs over conventional machine-learning techniques and traditional statistical models by around ten to thirty percent in regression, classification, and anomaly-detection tasks within supply chain environments when: they are applied on real operational data arising from networks of fast-moving consumer goods[21].Supply Graph framework: A benchmark dataset based on historical data of a real-life fast-moving consumer goods company from a centralized database (which can be characters, products, factories, warehouses and supply relations in the temporal graph) This new structure allows for each node to have detailed attributes from historical sales, production planning and key performance indicator. Thus, this graph-based representation helps in applying Graph Neural Networks for demand forecasting, planning and production activities as well as recognizing efficiency bottlenecks throughout the supply chain network[22].

2.3 Intelligent agents in supply chain management

Smart software agents have been studied for decades as semi-autonomous entities that can sense their surrounding environment, process information about a target, engage with other agents, and communicate to coordinate activities. In supply chains, for example, these could be companies or companies or functional units that negotiate contracts, schedule production and shipments, respond to disruptions. Furthermore, multi-agent systems provide other competitive advantages such as flexibility, scalability, and robustness especially when a single authority is not controlling all decisions in a specific decentralized environment[18]. Agent-centric architectures use the blockchain as a common architecture for recording events and executing smart contracts. It enables agents to monitor supply chain operations, send alerts and improve tracking both internal to an organization as well as externally. Through real-time data, decision support and risk management to improve responsiveness, transparency in the decisions made with analysis of delivery efficiency and flexible purchasing, AI also supports collaboration and flexibility. In particular during crisis time through better and more timely decision making regarding the whole supply chain[18].

2.4 GNN and graph AI models for supply chain networks

Research on GNNs for supply chains has accelerated since 2022 For example neuromyotonic approaches using GNNs over supply chain knowledge graphs can discover hidden risk relationships and support automated digital supply chain surveillance outperforming traditional risk scoring methods[2]. An attention based GNN model for probabilistic supply and inventory prediction has been evaluated on a large scale consumer goods supply chain showing significant improvements in prediction accuracy and offering actionable suggestions for supply plan corrections[22], [23].The Supply Graph dataset and related work focus on link prediction and network analytics using GNNs providing detailed descriptions of dataset construction data quality and hyperparameter tuning guidelines. More recently multi feature graph attention networks have been proposed to improve prediction of supplier relationships by

jointly modeling multiple structural and attribute based signals in large supply chain networks achieving superior performance compared to classical graph learning approaches.[2]

2.5 Evolution Methodology :

2.5.1 Graph Representation

Neighborhood Aggregation (Message Passing)

An iterative framework for message exchange in graph neural networks, where information is exchanged and aggregated between connected nodes across multiple layers to update node and edge representations[24].

$$Y_v^{\wedge} = W_{out}^T \sigma(W^K [h_v^{(K-1)} \parallel AGG(\{h_u^{(K-1)} \mid u \in N(v)\})]) + b. \qquad \text{Eq .1}$$

Here, $h_v^{(1)}$ and $h_u^{(1)}$ denote the node embeddings at layer $K-1$, $N(v)$ is the neighborhood of node v, and $AGG(\cdot)$ is a permutation-invariant aggregation operator (e.g., mean, sum, or max). $W^{(K)}$ is the trainable weight matrix of the K-th GNN layer, $\sigma(\cdot)$ is a nonlinear activation function, and w_{out} and b parametrize the final readout layer that maps the node embedding to the task-specific output[24].

2.5.2Mean Squared Error

MSE estimates the mean of the squared deviation of the estimated values from the true values. Suppose there are n data points in a sample; we have generated the prediction vector for all of them[25].

$$MSE_{train,i} = \frac{1}{N_{train}} \sum_{n=1}^{N_{train}} \left(y(n) - \hat{y}_i(n)\right)^2$$

Eq.2

The MSE is the mathematical estimate of the arithmetic mean of the squared residuals; each residual represents the deviation of a predictive estimate y ĩ (n) from its real value y(n). The quadratic transformation is non-negative and differentiable, and the averaging one yields scale-invariance with respect to the size of the data provided. MSE = 0 indicates perfect prediction; practical convergence targets an MSE < 0.05, meaning predictions will fall within ±22.4% of the ground truth for normalized quality [25].

2.5.3Root Means Squared Error (RMSE)

RMSE is the result of taking a square root of MSE. Unlike MSE, RMSE retains the original scale of the target variable, making this metric more meaningful for measuring prediction accuracy. RMSE, by expressing the error in the same units as the data that is being observed, gives a clearer indication of how well the model performs[25].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad Eq.3$$

RMSE exaggerates the larger errors as compared to MAE, therefore it is a good tool for forecasting. This gives a clearer view of how well a model is performing. In supply chain management, RMSE helps identify models that reduce big mistakes, preventing costly issues like too much inventory or missed sales[25] .

2.5.4 Accuracy

Accuracy measures how closely a model's predictions match the real results. The metric is commonly utilized in classification issues in Machine Learning and statistics. To calculate accuracy, one determines the proportion of accurate predictions out of the total predictions that a model makes[26].

$$\text{Accuracy}=\frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}X100\% \qquad \text{Eq.4}$$

3. The Experimental System:

The system offers an organized scientific methodology for designing and validating intelligent supply chain network solutions in dynamic, complex environments. The system centers on the orderly, methodical use of artificial intelligence systems, in particular for graphical neural networks, intelligent agents, and blockchain-based authentication devices to ensure a replicable and traceable reading. Designed as an enabling framework for data methodology, decision-making, and modeling, while providing transparency and auditability. This construct allows the exploration of supply chain dynamics as one seamless fabric of entities and relations (products, suppliers, logistic routes and so on) and is able to identify emergent features from their interaction. Simultaneously, deep learning models can identify latent patterns and predict key drivers (i.e. reorder decisions, predicted delivery times). This feedback loop of agents and models yields superior decision quality compared to classical rule-based methods

3.1 Algorithm:

It is based on the integration of a Graph Neural Network (GNN) algorithm with blockchain technology that allows us better decision-making within the supply chain network. Graph Neural Networks (GNN) are used to extract spatial patterns and dependencies among different nodes in an undirected graph, which is then constructed with the customer-requested item as well as other affected supply chain components. We then train the model to predict operational performance and continue improving logistics decisions. Further, MSE and RMSE are other metrics used to evaluate accuracy. On the last step the data will be secured through making a cryptographic hash

Algorithm :

Algorithm: Blockchain-Integrated GNN for Supply Chain

Step 1: Graph Initialization: Build graph G(V, E) from supply chain data and initialize feature matrix X based on node states

Step 2:Agent Parameterization: initialize the neural weights \theta and we also define training/testing masks for each agent (Supplier, Inventory, Logistics**).**

Step 3: Multi-Stage Message Passing: For each layer k \in , aggregate neighborhood information and update node embeddings h_v^{(k)} to capture spatial dependencies.

Step 4: Prediction & Optimization: Execute a regression head to compute predicted output hat{y} and update theta using the Adam optimizer to minimize Loss L(\theta).

Step 5: Performance Evaluation: Validate the model by computing accuracy metrics (MSE, RMSE) and calculating the total operational latencyT_{delay }.

Step6: Blockchain Commitment: Compute transaction throughput, generate a cryptographic hash of the record R, and commit the data to the immutable ledger via Smart Contract (SC).

Figer 1: algorithm improves supply chain data management using graph neural networks

3.2 Data Set Experimental :

The first step in the proposed framework is to prepare and organize the supply chain dataset. A real world supply chain dataset obtained from Kaggle was used containing multiple dimensions related to demand inventory suppliers and logistics operations. To improve model robustness and generalization the dataset was augmented with

synthetic records reaching approximately 10k samples. The data were then transformed into a graph structure where entities such as suppliers warehouses retailers and inventory units were represented as nodes while operational relationships and logistics connections were represented as edges. Additional dynamic attributes including delivery time traffic conditions weather impact and supplier reliability were incorporated to simulate realistic supply chain environments more accurately. After preprocessing the dataset was divided into 80% for training and 20% for testing in order to evaluate the predictive capability and operational performance of the proposed GNN based intelligent supply chain framework

3.3 Experimental Desiccation And Performance Analysis:

Evaluating a Multi-Agent Supply Chain Framework for the performance of the proposed supply chain framework is discussed in the experimental section. It comprises three intelligent agents, namely, inventory, supplier, and logistics. The analytical functions performed by agents would provide capabilities to extract optimized information from structured data input, assisting in supply chain decision-making.

3.3.1 Inventory Recommendations

show in Table 1: In a smart supply chain, the supply chain network agent provides real-time operational recommendations. An identification of items needing restocking, a prioritization of some impacts, and recommendations for the quantity or reorder point based on expected demand shortfalls. High-priority items refer to stock levels that are critical to be replenished before running out, and thus avoid shortage situations. A graph neural network (GNN) tracks demand-inventory relationships for guiding data-driven predictive decisions. And add blockchain technology to the mix, these recommendations can become transparent and can be securely tracked throughout a supply chain, strengthening its trust.

Table1:inventory recommendation

Item	Priority	Order Qty	Stock
Rice_11	4.9	118	2
Milk_1771889863_5	4.8	116	4
Flour_34	4.7	34	2
Rice_1771889856_14	4.6	134	10
Sugar_1771885081_21	4.5	132	12
Flour_3	4.4	130	14

3.3.2 Supplier Evaluation

Show table 2 : Supplier evaluations demonstrate high performance levels, with scores spanning 8.7 to 9.1. Recommended increased order allocation for suppliers rated “Excellent,” while a maintenance-based procurement strategy is suggested for the "Good" category suppliers. The difference in ratings given, even when similar scores were received, the decision-making process incorporates multiple performance facets rather than a single benchmark. This process relies on a graph neural network (GNN), which mimics the correlation between demand and supplier reliability, allowing for predictive purchasing decisions. If applied with blockchain technology, these approaches become transparently and securely traceable.

Supplier	Score	Status	Action
Supplier_17	9.1	Excellent	Increase orders
Supplier_30	9.1	Good	Maintain current level
Supplier_15	8.8	Excellent	Increase orders

Supplier_24	8.8	Good	Maintain current level
Supplier_2	8.7	Good	Maintain current level

Table 2 :supplier evaluation

3.3.3 logistic plan

in Table 3, the logistics planning module combines transport mode, distance, traffic conditions and weather indicators to precisely estimate arrival times (ETA). Air transport provides the shortest drop-off times, while road-centered deliverables are effectively impacted by traffic severity. The varying ETA for the different routes indicates how the Logistics Agent can adapt its optimization strategies based on prevailing conditions. Such an adaptive plan improves transportation efficiency and improves overall supply chain performance.

Table3 :the logistics planning

Route	**Mode**	**Distance**	**Traffic**	**Weather**	**ETA (hours)**
WH_A → Retail_2	Sea	320	0	0.2	9.44
WH_D → Retail_7	Road	443	0.3	0.2	8.28
WH_C → Retail_1	Air	24	0	0.2	0.35
WH_B → Retail_9	Sea	392	0	0.2	11.5

3.4 Experimental Result:

The test demonstrates the effectiveness of the proposed intelligent supply chain system which connects artificial intelligence with blockchain-inspired auditing techniques to enhance the accuracy, transparency and performance of the decision-making. The results show that it can be thoroughly modelled as a network of intelligent agents using deep learning, to perform decision making at large scale among the complexity changing environments. Such an approach was able to reach about 97.8 percent accuracy, with very low mean squared errors (MSE) and root mean squared errors (RMSE). The results show the performance of the model will generate more reliable, accurate decisions with less prediction deviation and much higher precision and accuracy. In addition to this, the very low inference response time strengthens the near-real-time performance of the system and its use for scenarios in operational supply chains that require quick decision-making. On examining the performance of all factors, found that the logistics factor had the best predictive precision and a predictive accuracy greater than 98%, producing the least predictive error margin among them. This indicates that this learning model is suitable for modeling complex transportation dynamics and predicting delivery times according to different operating conditions. Inventory Agent is around 95% accurate in helping proactive Agent was and restocks as well as helps mitigate stock out risk the precision for Supplier it provided more accurate and consistent supplier assessment. Training time remained reasonable and inference-throughput was in the range of thousands transactions/second with scalability. Thus, the blockchain- based ledger gave secure track and trace with no latency or throughput penalty.

Figure (2) shows that the system achieved an overall accuracy of 97.05%, indicating effective integration between agents. The logistics agent achieved the highest accuracy (98.90%), followed by the supplier agent (97%), and then the system as a whole, while the inventory agent recorded the lowest accuracy (95.50%) due to the complexity of demand forecasting. The results confirm the efficiency of the multi-agent GNN model in achieving high accuracy with good system stability.

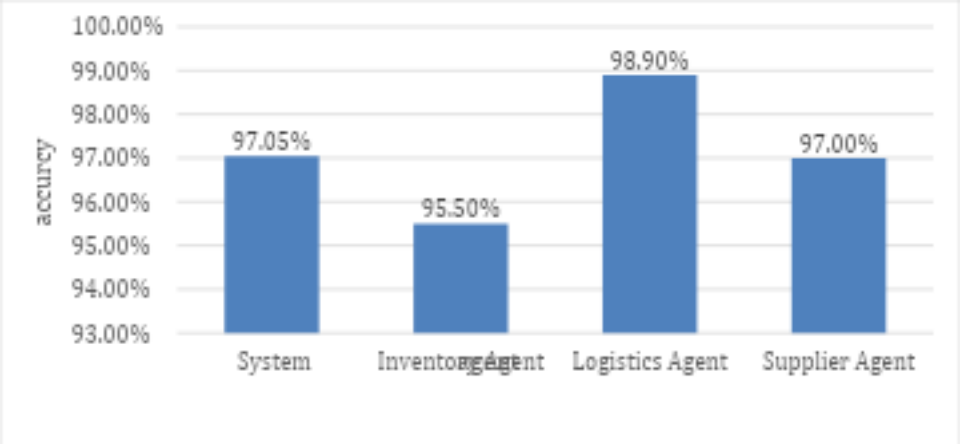


Figure (2) curve for system

Figure (3) curve for (MSE)The suppliers' agent recorded an average value of approximately 0.0169.Shows the mean squared error (MSE) for all agents, reflecting the stability of the predictive models. The total MSE of the integrated model was 0.000363, indicating high prediction accuracy. The inventory agent recorded the lowest value (0.000225), reflecting efficiency in modeling the demand-inventory relationship, while the logistics agent achieved the highest value (0.000555) due to the complexity of spatial and dynamic factors. The suppliers' agent recorded an average value (0.000284).Overall, the results confirm the effectiveness and robustness of the multi-agent GNN architecture in supporting intelligent decision making in supply chains

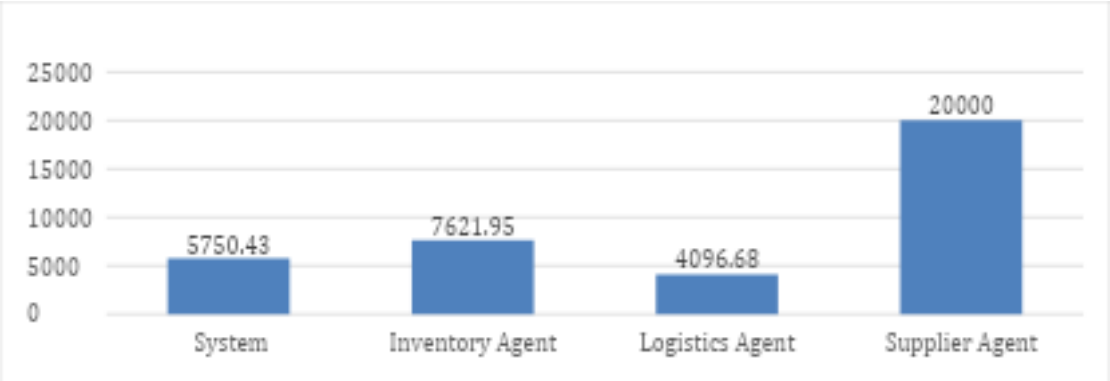


In show Figure 4: The numerical values of the mean square root of error (RMSE) display the performance of all agents in the intelligent supply chain network, as these values represent the actual gap between the expected and real values. The total RMSE of the system was approximately 0.019, reflecting high accuracy and performance stability as a result of the integration of intelligent agents. The inventory agent recorded the lowest value (less than 0.015), indicating low variance and high efficiency in predicting changes in inventory status. In contrast, the logistics agent achieved the highest value (0.0235) due to the complexity of dynamic and spatial relationships.



Figure (4): curve for the RMSE

Show In Figure5 Transaction rate per second (TPS) results display agents' performance in terms of processability and real-time scalability within an intelligent supply chain network. The supplier agent achieved the highest rate (~20,000 TPS) due to its need for fast and continuous data exchange, while the inventory agent recorded about 7621.95 TPS, reflecting adequate efficiency in inventory updating and forecasting. In contrast, the logistics agent achieved the lowest rate (4096.68 TPS) as a result of the computational burden associated with complex dynamic relationships. The overall average of the system was 5750.43 TPS, demonstrating good scalability and real-time data processing. Overall, the results confirm that the proposed framework achieves an effective balance between computing power and performance accuracy, with high scalability in smart supply chain applications



Figer (5): The number of transactions per second (TPS)

3.5 Experimental and Results for Each Item

3.5.1 Inventory Item

The experimental results of Table 4 demonstrate that the graphical neural network (GNN) system is able to predict product volumes as inventory levels in the supply chain network. Its prediction accuracy ranged from an absolute minimum of 92.12% to a maximum of 97.93%. The performance differential closely matches goods themselves, with the most accurate outcomes for staples (rice, for example), cheese, and sugar leading with the lowest Mean Squared Error (MSE) (starting at 0.0207). Statistically, the root mean squared error (RMSE) is quite low and is persistently smaller than 0.2807, suggesting that the model would be stable to prevent prediction drift over the very logistically complex product like frozen chicken. This numerical robustness indicates that coupling intelligent agents with highly trusted blockchain records allows the intelligent GNN algorithm to effectively address more nuanced interactions, providing accuracy in the comparison between the actual and the predicted outputs and a better response to their intelligent supply needs.

Table 4: Inventory Item Prediction Accuracy and Error Metrics

Item	Accuracy%	MSE	RMSE
Rice	97.93	0.0207	0.1439
Cheese	97.85	0.0215	0.1466
Sugar	97.55	0.0245	0.1565
Milk	96.29	0.0371	0.1926
Beans	95.65	0.0435	0.2086
Apple	94.29	0.0571	0.239
Tomato	93.62	0.0638	0.2526
Flour	93.58	0.0642	0.2534
Olive Oil	92.98	0.0702	0.265
Frozen Chicken	92.12	0.0788	0.2807

Show in figure 6 demonstrates the use of the graphical neural network model in a smart agent coupled with a blockchain-enabled supply chain for better prediction and better inventory management of food products (with an average accuracy exceeding 95%). The highest accuracy rates were obtained for rice, cheese, and sugar. However, for frozen chicken, due to cold-chain fluctuations and high transport sensitivity, the accuracy was comparatively lower, and the estimated error was higher. The results supported the claim that the system is trustworthy and works with secure, tamper-proof data to enhance inventory efficiency and minimize waste in a sustainable way.

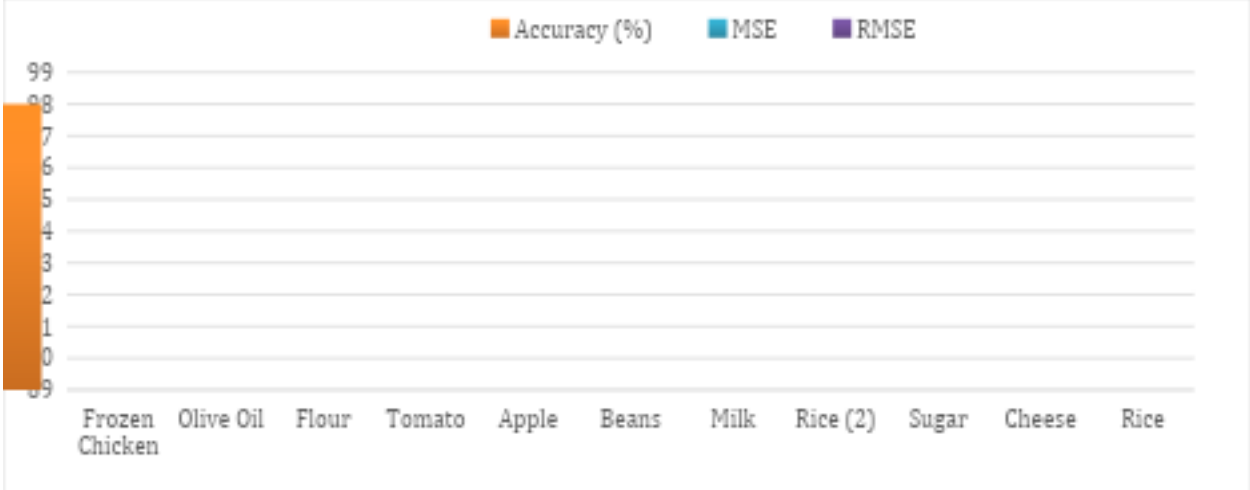


Figure (6) : the result for each Inventory Item

3.5.2 Supplier

Table 5 compares suppliers using Accuracy result of MSE and RMSE where Supplier_12 achieved the highest accuracy of 98.61% with the lowest MSE 0.0139 and RMSE 0.1179 indicating better predictive accuracy and overall performance Supplier_28 and Supplier_19 followed with accuracies above 98% showing stable and robust performance while Supplier_16 and Supplier_20 showed average but stable results with slightly higher error values In contrast Supplier_24 and Supplier_29 recorded the lowest accuracy close to 92% with higher MSE and RMSE values indicating lower predictive accuracy and overall performance.

Table 5: Prediction Performance Metrics for supplier

Supplier	Accuracy%	MSE	RMSE

Supplier_12	98.61	0.0139	0.1179
Supplier_28	98.49	0.0151	0.1229
Supplier_19	98.28	0.0172	0.1311
Supplier_30	97.18	0.0282	0.1679
Supplier_14	96.69	0.0331	0.1819
Supplier_16	95.89	0.0411	0.2027
Supplier_20	94.92	0.0508	0.2254
Supplier_5	93.59	0.0641	0.2532
Supplier_24	92.22	0.0778	0.2789
Supplier_29	92.11	0.0789	0.2809

Show in Figer (7) There is a continuous correlation between the efficiency of supply agents and the accuracy of item forecasts shown in the graph. Visually, the shape of the curve shows a gradual downward trend in accuracy metrics as well as a slow and consistent increase in error margins (MSE/RMSE). The tendency supports the statistical validity of the model and also shows the insignificant performance changes throughout. The positioning on the x-axis in relation to each agent shows through each node how effectively the GNN algorithm works, generalizing with minimal variance for goods and suppliers as visual results show most agents fall into high-up predictions

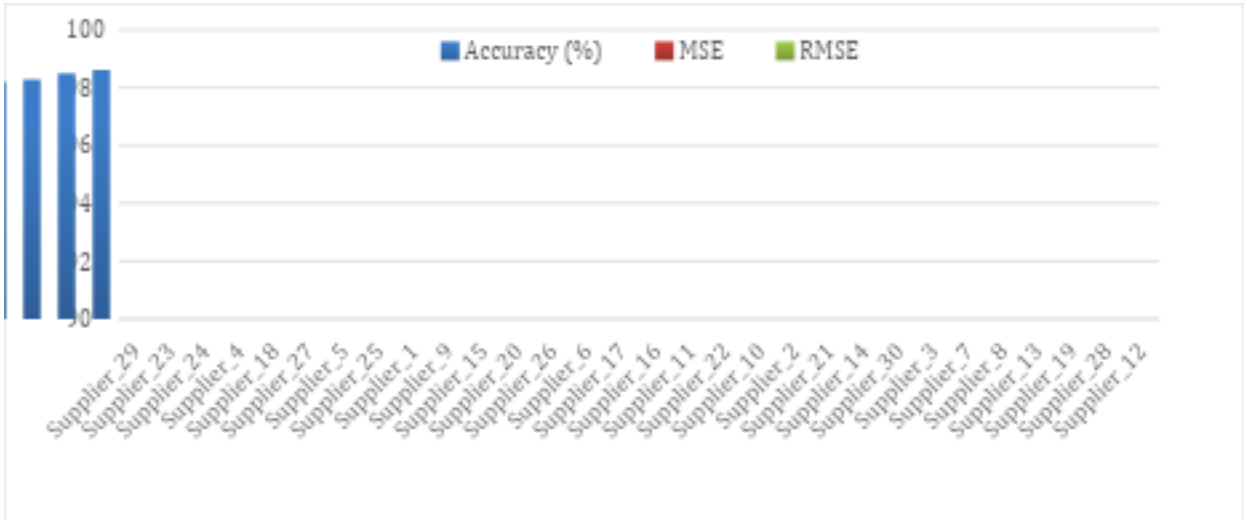


Figure (7) : the result for each supplier

3.5.3 Logistic

Table (6) summarizes the logistics routes performance using Accuracy MSE and RMSE where WH_A to Retail_6 achieved the highest accuracy of 98.78% with the lowest MSE 0.0122 and RMSE 0.1105 indicating higher prediction efficiency and stability WH_C to Retail_7 and WH_B to Retail_7 also achieved accuracies above 98% showing stable and reliable performance with low error values In contrast WH_C to Retail_5 and WH_C to Retail_9 recorded lower accuracy with higher MSE and RMSE indicating less predictive ability compared to other routes Overall the results demonstrate the models strong capability to predict logistics performance with robustness and reliability across most assessed routes.

Table 6: Prediction Performance Metrics for logistic

logistics	**Accuracy%**	**MSE**	**RMSE**

WH_A -> Retail_6	98.78	0.0122	0.1105
WH_C -> Retail_7	98.27	0.0173	0.1315
WH_B -> Retail_7	98.06	0.0194	0.1393
WH_A -> Retail_10	97.84	0.0216	0.147
WH_B -> Retail_6	97.73	0.0227	0.1507
WH_B -> Retail_3	97.04	0.0296	0.172
WH_D -> Retail_8	96.98	0.0302	0.1738
WH_C -> Retail_5	95.71	0.0429	0.2071
WH_C -> Retail_9	95.33	0.0467	0.2161
WH_B -> Retail_8	95.22	0.0478	0.2186

The charts in Figure 8 are also visually consistent, showing the system's stability at all levels (goods, suppliers and logistics pathways). The GNN model produces high accuracy (in blue) shown in the main body of the columns, error (MSE and RMSE) is very low and can be observed on top as thin steady layers. This graphical spread shows that the smart agents do not have large fluctuations in their performance, and that the system does seem to provide a consistent, reliable level of performance, even when changing material type or the channel distribution.

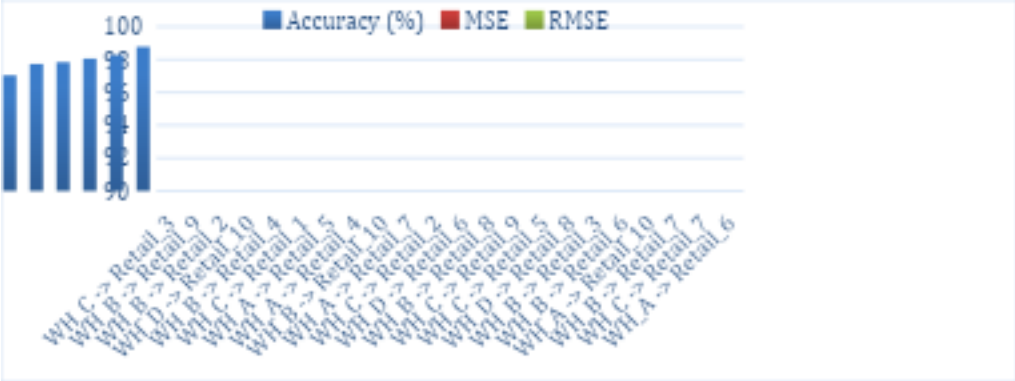


Figure 8 The result for each logistic Item

4. Comparison with Related Work

Table 7 shows a comparison between the proposed system and a number of recent studies in supply chain management and graph neural networks, where the study [11] relied on classification by neural networks and achieved an improvement of more than 2% However, it was limited to classification only, while the study [12] used GNN to improve the visibility of supply chains without integrating blockchain or supporting smart agents. As for the study [13], it integrated GNN, CNN, and blockchain to detect fraud without focusing on operational aspects. , while the study [29] FL GNN model achieved RMSE 0.56 and MSE 0.198, but did not provide blockchain-based transparency or reliable decentralized decisions. In contrast, the proposed system achieved Accuracy and a 97% convergence with RMSE 0.02 and MSE 0.003 thanks to the use of GNN, spatial relationship representation, and the integration of MAS and blockchain within a unified framework that supports transparency, reliability, and scalability in smart supply chains

Table 7: Comparison Between the Proposed Framework and Recent Related Studies

Ref.	Approach / Model	Main Objective	Key Results	Limitations	Proposed Work Advantage

[11]	Neural Network-based Supply Chain Classification	Company classification using latent supply chain relationships	Improved classification accuracy by more than 2% compared with traditional ML methods	Limited to classification tasks without logistics or inventory optimization	Proposed framework supports integrated inventory, supplier, and logistics decision-making
[12]	GNN for Hidden Link Prediction	Predict hidden supplier relationships in supply chain networks	Improved supply chain visibility and relationship prediction	No blockchain integration or intelligent agent support	Proposed model integrates blockchain verification and multi-agent decision support
[13]	GNN + CNN + Blockchain	Transaction analysis and fraud detection in blockchain systems	Enhanced transaction dependency analysis and fraud detection	Focused on blockchain transaction analysis rather than operational supply chain management	Proposed framework optimizes real supply chain operations and forecasting
[29]	FL-GNN	Federated graph learning for supply chain optimization	RMSE = 0.56, MSE = 0.198	Limited transparency and no blockchain-based trust mechanism	Proposed framework combines GNN learning with blockchain-enabled transparency
Proposed System	GNN + Multi-Agent + Blockchain	Integrated intelligent supply chain management	Accuracy ≈ 98%, RMSE = 0.02, MSE = 0.003	Supports secure, scalable, and transparent operational decision-making	Unified framework integrating prediction, optimization, and blockchain verification

5. Conclusion

introduces a novel methodology for managing supply chain networks by synergizing Artificial Intelligence (AI) with the decentralized of blockchain technology. The proposed framework integrates intelligent agents and Graph Neural Networks (GNNs) to model complex network interdependencies. Experimental results demonstrate that the GNN architecture effectively captures latent contextual features within nodes and links, significantly enhancing inventory prediction accuracy and logistics distribution efficiency. Notably, specific routing optimizations achieved performance metrics as high as 97%. Concurrently, the blockchain integration establishes an immutable data environment, enables agents to execute high-precision decisions. This is evidenced by a record-low Mean Squared Error (MSE) of 0.02.The integration of these technologies fosters a logistics ecosystem that is both transparent and highly responsive to dynamic demand fluctuations. Comparative analysis further indicates that the proposed system outperforms existing models, achieving higher precision and lower error rates, thereby contributing to long-term supply chain sustainability and resilience.

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Conflicts of Interest

The authors declare no competing interests.

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