IoT and AI in Smart Logistics: Enhancing Decision-Making for Real-Time Supply Chain Transparency

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Abstract: In today's globalized and highly interconnected markets, supply chain transparency has become a cornerstone of effective business operations. With real-time supply chain insight, businesses can meet changing consumer needs, manage resource allocation, and react effectively to interruptions. The aim of the research is to improve supply chain transparency and decision-making, which are crucial in modern logistics systems. By offering predictive analytics, adaptive risk mitigation, and real-time tracking, the combination of artificial intelligence (AI) and Internet of Things (IoT) technology provides significant solutions. The data gathered from IoT devices, such as RFID tags, GPS sensors, and environmental monitors, provide continuous data streams across various supply chain stages, including suppliers, manufacturers, and logistics providers. Data requires preprocessing for effective analysis, data cleaning, removing noise and redundant entries from raw IoT data streams. To process and analyze this complex data, this research proposes an Efficient Golden Eagle mutated Light Gradient Boosting Machine (EGE-Light GBM) model is to predict potential risk, optimize routes, and enhance overall supply chain transparency. This method offers corresponding decision support by properly forecasting possible supply chain risks. Comparative analyses demonstrate that this approach outperforms traditional methods and baseline models, achieving significant improvements in transparency, reliability, and operational efficiency.

Keywords: *Smart Logistics, Decision-Making, Supply Chain Transparency, Internet of things (IoT), Efficient Golden Eagle mutated Light Gradient Boosting Machine (EGE-Light GBM)*.

Introduction

Business organizations are increasingly overwhelmed by the various forms of transactions, customer record details, communications, and internet-of-things (IoT) data streams from various sources of their operations, creating complex and dynamic environments for data, characterized by high in volume, high in velocity, and high in diversity. Traditional decision-making framework that rely solely on databases, are often inadequate for such complex systems. Such volatilities have occurred in the corporate world that coupled with regular shifts in the market condition, consumer demand, and technology has made effective decision-making an integral element of strategic management [1]. The three primary drivers for small and medium-sized enterprises (SME) growth are productivity, quality, and competitiveness. A business can become competitive in the market only when it concentrates on the SC management This approach provides a foundation for business groundwork for exporting total or part elements of the chain. E-commerce involves more reliable shipping and greater inventory turnover, with products restocked at regional forward staging hubs which are close to their customers. A large number of third-party logistics (3PL) companies have emerged to support this complex supply chain by offering a wide variety of services [2].

All the processes related to fulfilling the customer needs contribute to forming a supply chain. There are three essential flows including materials, information, and money. Efficient flow management is essentially a key factor in the effective organization of a supply chain [3].

The supply chain management (SCM) heavily relies on well-analyzed data. However, since the logistics networks of the real world are dynamic and stochastic, data collection becomes challenging. To sufficiently represent the context of the problem, contemporary decision support systems must be required to consider data collection uncertainty, as model simplicity must be preserved for the proper exploitation of systematic insights [4].

With globalization and outsourcing taking hold, supply chains have grown in size and complexity, making them more susceptible to disruptions. Supply chains must adopt innovative approaches to both quickly and inexpensively respond to changing market conditions that are rapidly developing. Information flow in supply chains has become more complex due to global competition, a reduction in inventory, and customization at different levels [5]. As customers' expectations become more challenging and the world keeps moving at an incredible pace, a business must discover ways to improve supply chain, inventory management, and logistics processes in the fast-moving market. Most global supply chains in modern times, however, outstrip traditional optimization techniques with too many rigid rules and archaic models, leaving the whole complex supply chain functioning in an unstable environment with uncertain variations in demand and unexpected interruptions along with multiple stakeholder relationships [6].

Smart logistics integrates interrelated components that interact in real-time to provide extensive visibility into the whole supply chain process, it represents a paradigm leap in supply chain management. SCM can use smart logistics for more than just tracking shipments or inventories. It covers several phases of the supply chain, such as last-mile delivery, manufacturing, warehousing, and procurement. Businesses may improve satisfaction among clients through quicker and more dependable deliveries, automate inventory replenishment, optimize route planning, and predict demand changes by integrating information into these stages [7].

Research Objective

The research aims to improve supply chain transparency and decision-making in contemporary logistic systems by combining artificial intelligence (AI) and the Internet of Things (IoT). It is attempting to integrate real-time data from IoT devices, predictive analytics, and adaptive approaches to risk avoidance in order to anticipate possible danger, optimize routes, and boost overall operational efficiency.

Related work

To identify and assess the key determinants that have impacted the choice of digital vendors for improved supply chain quality management (SCQM) [8]. The combined weighted aggregated sum product assessment (WASPA) method was applied in a critical appraisal of digital suppliers based on parameters such as digital innovation, resilience, sensitivity, sustainability practices, and expertise. The results indicated that the knowledge of the suppliers is the most important criterion that affects the selection of a digital supplier. Supplier S8 has been found to be the best supplier among the factors mentioned. It has concentrated on a specific group of suppliers and cannot be generalized for various categories of industries. The possibilities and significance of AI in SCM were analysed, with a special emphasis on AI decision-making functions and the different levels of AI integration within the supply chain [9]. The posited a conceptual framework that was based on blending sociotechnical views and multidisciplinary partnerships to determine AI integration in SCM. Machine learning (ML) techniques were utilized to improve the various phases of the supply chain, enhancing effectiveness and transparency. The proposed AI integration framework in SCM has not been empirically tested nor implemented in practice.

To assess the effectiveness of AI in supply chain performance and resilience especially in complex and changing environments [10]. The research based on organizational information processing theory (OIPT) conceptualized AI applications in a supply chain. The results were positive, showing enhanced resilience with increased long-term efficiencies of supply chain. The empirical research was confined to an elaboration on the description of the particular AI technique or industry differences, which restrict its generalizability. Explored the green supplier selection for optimizing waste and minimizing the utilization of resources for sustainable supply chains [11]. The approach suggested a Linear Diophantine fuzzy (LIDF) framework with integrated aggregation managers to provide an efficient method of green supplier selection. LIDF was reported to have the advantages of facilitating good decision-making along with customer satisfaction, and minimization of the cost. However, the method has the disadvantages of challenges in integrating data in real-life and dependence upon accurate input.

The CNN approach was employed to enhance the efficiency of an AI-based technique classifying containers based on factors such as weight, destination, special requirements, and price [12]. The method implemented CNN image-based classification followed by further ranking of the containers. In each tested instances of the model, high accuracy was determined along with the enhancement of the efficiency in sorting the containers. The performance results could vary based on the quality of data and constraints of real-time computations. The strategy improves the avoidance of problems and dynamic path forecasting for logistics path planning and management in complicated situations [13]. The long short-term memory (LSTM) models for predicting the behavior of obstacles and the Dijkstra algorithm to plan paths and 3D CNN for representing objects to avoid. The approach significantly surpasses traditional approaches with better path prediction and improvement of obstacle avoidance accuracy. The model's performance would be inhibited in extremely dynamic contexts by restrictions on the level of complexity in real-time data processing. To investigate the use of block chain, and AI-powered smart supply chains with security related to IoT device data protection [14]. An AI-driven platform integrating block chain was utilized to safeguard data flows in smart supply chains, emphasizing the mitigation of risk. Integration enhanced supply chain effectiveness but came with security nuisances related to handling sensitive information, which called for stronger security protocol. Security threats posed by the complexity and the sensitivity of information processed by IoT devices might expose vulnerabilities within block chain-based systems. The optimized logistics within an intelligent transportation system utilized a CNN model to extract complex patterns from sensory data, enhancing vehicle classification accuracy [15]. The model provided sensory inputs from public transportation, and automobiles to identify intricate patterns of precise vehicle classification. For real-time application in large-scale systems, the accuracy of the data affected the effectiveness of the model, which could necessitate a large amount of computing power.

Methodology

The section addresses the framework and elements of the proposed method that uses an integration of IoT devices across the supply chain, capturing data in real-time. After data pre-processing, which includes cleaning and min-max normalization, it employs a risk-predicting route optimizer using an efficient golden eagle mutated light gradient boosting machine (EGE-Light GBM) for optimizing the process. Figure 1 shows proposed flow of EGE-Light GBM for enhancing supply chain efficiency and predictive analytics.

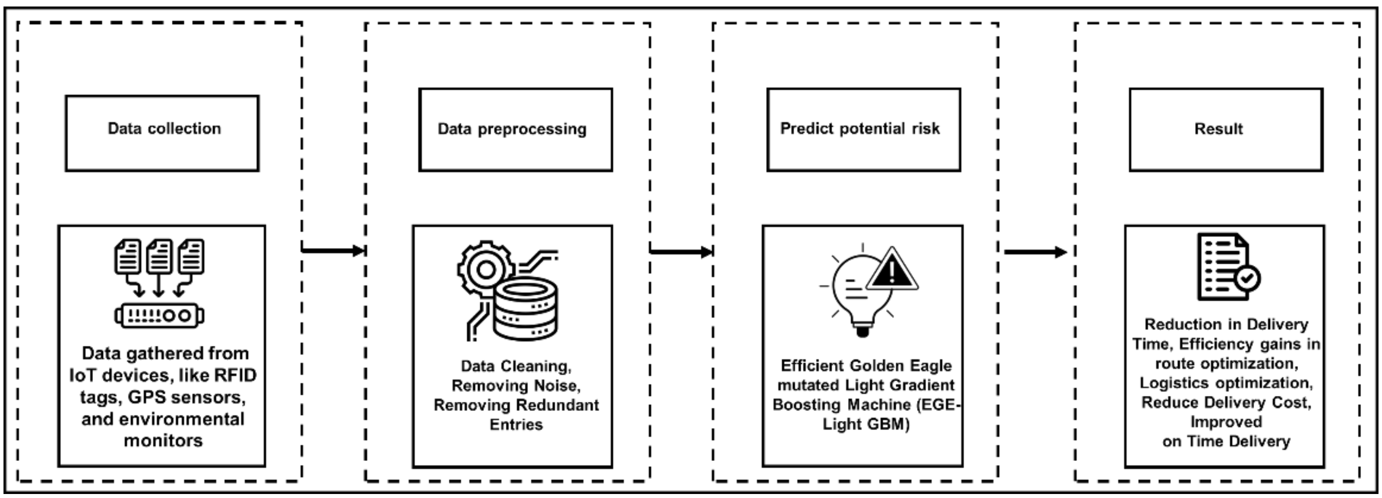

Figure 1 Block diagram for proposed flow

Dataset

The Kaggle dataset [16] collects real-time supply chain data from several logistical stages using Internet of Things (IoT) technologies. It contains details such as transaction IDs, supply chain phases, parties involved, environmental factors, shipment destinations, and delays. The information obtained from this dataset is intended to help with risk factor identification, route optimization, delivery status prediction, and disruption forecasting. It provides systematic understanding of supply chain, allowing companies to use predictive analytics to improve decision-making and operational efficiency.

Data preprocessing

Cleaning and converting raw data into a structured format appropriate for modeling is known as data preprocessing. It includes steps such as handling and missing value, encoding categorical variables and removing outliers to improve the quality and accuracy of machine learning (ML) models.

Data Cleaning

It is the process of identifying and fixing unintentional faults in information to ensure the dataset's dependability and appropriateness for evaluation. This includes several procedures: handling missing or incomplete values, removing duplicate values, and normalizing inconsistent formats. The refined data has to be accurately used for determining risk, and routing optimization, thereby contributing to better decision making and enhanced efficiency of the supply chain process.

Removing Noise

Noise is defined as the irrelevant or erroneous data values resulting from source such as malfunctioning sensors and environmental conditions. Outliers, which can be discarded, help ensure that only clean relevant data is retained to enable an accurate reflection of the patterns or trends of the underlying patterns or trends.

Redundant Entries

This step identifies duplicate or redundant information that impact the skew analysis to be done. Most redundancies arise in datasets as an error when collecting data or merging files. Elimination of these errors creates a much straighter dataset; hence, their processing and computation can be accomplished more efficiently with accuracy.

Prediction using Efficient Golden Eagle Mutated Light Gradient Boosting Machine (EGE-Light GBM)

EGE-Light GBM is a combination of EGE and the gradient advancing framework of Light GBM, where the hybrid methodology utilizes the power of optimization abilities of the Golden Eagle algorithm for fine-tuning the hyperparameter of Light GBM in enhancing its prediction capabilities. This means the model will dynamically adapt to different patterns of mutation in data; therefore, in real-time, risk prediction and route optimization become more robust and reliable. Hence, EGE-Light GBM performs superior to existing models in supplying decisions and improved operational efficiency.

Light Gradient Boosting Machine (Light GBM)

The decision tree method serves as the foundation for the improvement in architecture known as light GBM. Its benefits include high training speed and parallel processing efficiency, reduced memory usage compared to traditional methods, and the ability to process batch data swiftly in a distributed environment. Furthermore, Light GBM uses a leaf growth method to slow the expansion of the leaf nodes and offers a histogram to choose characteristics. Equation (1) shows that the light GBM uses the decision tree as the base learner,

$$G_S(w) = \sum_{S=1}^{S} G_S(w) \qquad G_S \in J \tag{1}$$

Simulation process, where, $G_S(w)$ indicates the transformation or output at each time step t the optimizing logistics in intelligent transportation system, reflect the cumulative effect of various model parameter such as, time, enhancing precision, effectiveness of vehicle decision making processes. The square difference of approximation to fit model is shown in equation (2).

$$g_S(w) = \arg min \sum \left(q_s - g_s(w)\right)^2 \tag{2}$$

$g_S(w)$ is the predicted value for a given input x, and q_s is the observed or target value. Find the optimal value of $g_s(w)$ those best fits for given data. Equation (3) recursively refines the output by incorporating both current transformation and previous results.

$$G_S(w) = g_S(w) + G_{s-1}(w) \tag{3}$$

A recursive relationship $G_S(w)$ is the output at time step t and $g_S(w)$ indicates the previous step result. It shows how system incorporates past output to refine or adjust the current decision-making process. The crucial in optimizing logistics and transportation, where past data influences real-time decisions.

Efficient Golden Eagle (EGE)

The EGE optimization is specifically focused on representing the golden eagles' strategy of hunting to optimize decision making. It is highly efficient in the area of solving complex optimization problems efficiently, which relies on high-speed convergence and adaptability. EGE has the following benefits over alternative metaheuristic algorithms.

Natural inspiration: The natural hunting habits of golden eagles served as the model for EGE. This motivation results in original and creative search tactics that could excel in specific problem domains.

Diversity maintenance: Mechanisms to preserve population variety are incorporated into EGE. This can enhance the algorithm's capacity for global exploration and assist avoiding an early convergence to less-than-ideal solutions.

Efficiency: EEG can be used to solve optimization issues involving costly assessments of fitness or huge exploration spaces, because of its highly computational design.

Adaptability: Numerous optimization problems can be solved with EGE, and its specifications can frequently be changed to customize its behavior for the specific issue. The golden eagle impressive hunting skills, relies on circular trajectories while hunting. The natural strategy similar to optimization techniques highlights the connection between nature's problem-solving and algorithmic advancement. Equation (4) shows the spiral motion of the golden eagle.

$$E = \{1,2,3, \dots, PS\} \tag{4}$$

PS Contains the total number of elements in set E. In other words, if PS=10, then E will be the set of numbers$1, 2, 3, \dots$ 10. Depending on the model, PS could be an iteration number, data points, or any other variable that denominates the range of the set with working. The scale form of the hyper plane equation is displayed in equation (5).

$$l_1 z_1 + l_2 z_2 + \cdots + l_m z_m = O \Rightarrow \sum_{i=1}^{m} l_i z_i = O \tag{5}$$

Linear combination of variables $z_1, z_2 \dots z_m$ with corresponding coefficient $l_1, l_2, \dots l_m$ equaling zero. The $\sum_{i=1}^{m} l_i z_i = O$ is a more compact way to represent the weighted sum of the variables that equals zero. The fixed variable's amount is determined using the following equation (6) if the target vector's duration i is not greater than zero.

$$\sum_{i=1}^{m} a_j z_i = \sum_{i=1}^{m} a_i^s \tag{6}$$

The weighted sum of some variables factors is z_i is equal to a certain amount of optimized or adjusted coefficientsa_i^s. This might be related to the efficiency or effectiveness of a process within logistics optimization objective. Equation (7) provides a general idea of the direction, where the cruise hyper plane is headed.

$$\vec{F}_j = \left(f_1 = random, f_2 = random, \dots, f_l = \frac{O - \sum_{i,i \neq l} a_i}{a_l}, f_l = random \right) \tag{7}$$

The parameters $f_{1,} f_{2 \dots} f_{1,}$ are randomly initialized and calculated for the l element by adding the other parameters such that the objective function O is balanced. This is a result of dynamic adjustment of the parameter a_i in the optimization of logistics with intelligent transportation systems, improve efficiency and accuracy. Equation (8) represents the golden eagle phase vector's representation.

$$\Delta z_j = \vec{y}_1 c_b \frac{\vec{A}_j}{\|\vec{A}_j\|} + \vec{y}_2 c_d \frac{\vec{F}_j}{\|\vec{F}_j\|} \tag{8}$$

Here, $\|\vec{A}_j\|$ indicates the attack vector's Euclidean norm, $\vec{y}_1$ and $\vec{y}_2$ are shown as random vectors throughout the [0,1] period, $\|\vec{F}_j\|$ represents the cruise vector's Euclidean norm, c_d is the coefficient of cruise and c_b is the coefficient of attack. Equation (9) defines the Euclidean norm of the cruise and assault vectors.

$$\|\vec{A}_j\| = \sqrt{\sum_{i=1}^{m} a_i^2} \tag{9}$$

This equation can be applied to determine the size of a vector that illustrates a set of data points or features. Magnitude vector $\vec{A}_j$ and a_i^2 are the components of vector. Hence, this approach allows us a to approximate how strong different parameters are in maximizing supply chain efficiency. The location of the golden eagle is determined using the step vector as shown in equation (10).

$$z^{s+1} = z^s + \Delta z_j^s \tag{10}$$

Where z^{s+1} denotes the updated value of the parameter z at iterations $+ 1$, based on the previous value z^s and the change Δz_j^s. It describes the iterative optimization process in the model. Figure 2 shows the EGE strategic approach to optimizing routs and resource allocation in complex systems.

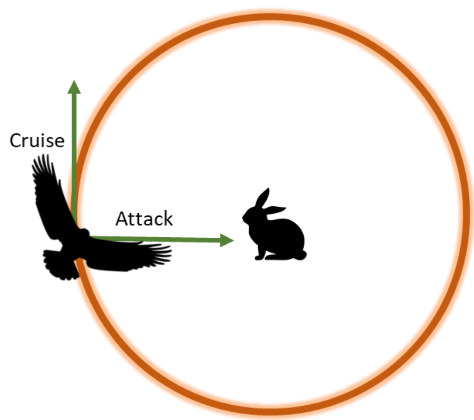

Figure 2 Simulation of EGE optimization

EGE-Light GBM enhances the transparency in the supply chain by classifying risks, parameter optimization, and improved decision-making, offering real-time predictive insight for advanced adaptable resilient supply chains shown in algorithm 1.

Algorithm 1 Efficient Golden Eagle Mutated Light Gradient Boosting Machine (EGE-Light GBM)

Step 1: Light GBM Initialization
Initialize Light GBM Model (X, y)
$Gs(w)$ = Update Tree $(Gs(w))$
For $s = 1$ to$S$:
Update Model with $G\_s(w)$
Step 2: EGE Optimization
Initialize EGE Parameters (Population$E$, Random Positions)
For each iteration:
For element in$E$:
Accept or Reject position based on fl
Step 3: Combine Light GBM and EGE
If (Light GBM Model optimized and EGE optimized)
Return Combined Model (Light GBM Model, EGE)

Else if (Light GBM Model optimized)
Return Light GBM Model
Else if (EGE optimized)
Return EGE

Results and Discussion

The findings are presented; along with a thorough analysis of the performance improvement across a range of measures is provided by contrasting the suggested strategy with current practices. The research employed Python 3.11.2 to implement and execute the required algorithms. The experiments were conducted on a high-performance desktop configured with 62 GB RAM and an AMD Ryzen 5900X processor running Windows 11. The setup provided enhanced computational capabilities, facilitating the evaluation of the proposed optimization techniques under various conditions and ensuring reliable performance during extensive simulations.

Performance Evaluation

The evaluation of performance shows improvements such as reductions in delivery time due to optimized routing and enhanced logistics effectiveness. Route optimization minimizes long delays through the sophisticated algorithms, which facilitates faster delivery. AI-driven methodology integration improves logistics performance, making workflows less substantial and also providing the saving of costs and overall smoothing of the supply chain process. Convolutional Neural Networks (CNNs) and Ant Colony Optimization (ACO) with block chain [17], autoregressive integrated moving average (ARIMA) and exponential smoothing state space model (ETS) (ARIMA and ETS) [18] are used to compare and evaluate the performance of proposed EGE-Light GBM.

Reduction in Delivery Time

Delivery time can be defined as the time needed to deliver the product or service to the final customer or consumer after an order has been submitted. It will typically begin upon confirmation of an order and be completed when a product is received by a customer. The result shows the improvement across all metrics in the proposed model, such as a reduction in average delivery time which is 14hrs, and fewer customer complaints 6. Table 1 shows the performance metrics of the existing and proposed methods.

Table 1 Comparison of Key Performance Metrics Between ACO+ CNN + Block Chain and Proposed Model.

Metric	**ACO+ CNN + block chain [17]**	**[EGE-Light GBM]**
Average delivery time	18	14
On-time delivery rate	95%	98%
Late deliveries	5%	3%

Delivery accuracy	98%	98.5%
Customer complaints	10	6
Delivery cost per mile	2.00	1.80
Carbon emission	40	35

The performance of two models, ACO + CNN + Blockchain and EGE-Light GBM, is contrasted in the table using a number of delivery measures. In the majority of areas, such as lowering average delivery time (14 compared to 18), delivery delays (3% compared to 5%), and complaints from clients (6 compared to 10), EGE-Light GBM performs better than ACO + CNN + Blockchain. While both models demonstrate great delivery accuracy (98% compared to 98.5%), EGE-Light GBM reduces carbon emissions (35 compared to 40) and has a little higher on-time delivery percentage (98% compared to 95%) and reduced delivery costs (1.80 compared to 2.00).

Efficiency gains in route optimization

Route optimization is achieved through advanced algorithm, reduced delivery cost and improving on-time performance. The proposed model shows improvement across all metrics, with notable reductions in average travel distance (decrease from 80 to 70), fuel consumption (decrease from 400 to 350), and vehicle idle time (decrease from 30 to 25). It also reduces route deviation by (from 5% to 3%) and delivery over time by (from 5 hours to 3 hours), while improving vehicle utilization rate by (from 85% to 90%). The model also decreases total route planning time by (15 hours to 12 hours) and reduces vehicle maintenance costs by (12,000 to 10,550). Table 2 shows the improvement in supply chain efficiency with EGE-Light GBM over ACO+ CNN + block chain.

Table 2 Key Metric Comparison of existing and proposed algorithms

Metric	**ACO+ CNN + block chain [17]**	**[EGE-Light GBM]**
Average travel distance	80	70
Fuel consumption	400	350
Vehicle idle time	30	25
Route deviation	5	3
Vehicle utilization rate	85	90
Delivery over time (hours)	5	3
Total route planning time (hours)	15	12
Vehicle maintenance	12,000	10,500

Comparison phase

The effectiveness of a proposed method is evaluated and it outperforms traditional approaches. The Performance metrics such as delivery cost and on-time delivery are compared, as indicated in table 3.

Table 3 Comparison of delivery cost and on-time delivery across traditional and proposed methods

Metric	ACO + CNN+ block chain [17]	ARIMA and ETS [18]	Proposed [EGE-Light GBM]
Delivery cost	2	2	1.7
On-time delivery	97%	94%	98.2%

The table shows that all the above critical logistic metrics have been compared across the performance of ARIMA and ETS, ACO + CNN + block chain, and Proposed EGE-Light GBM. The delivery cost was reduced to 1.7, and on-time delivery improved to 98.2% using EGE-Light GBM compared to the above two methods. For the same, ACO + CNN + Block chain gets delivery cost of 2 and on-time delivery of 97%, and for ARIMA, ETS it is on-time delivery at 94%. The proposed model proves to have high efficiency with reduced cost, as shown in figure 3.

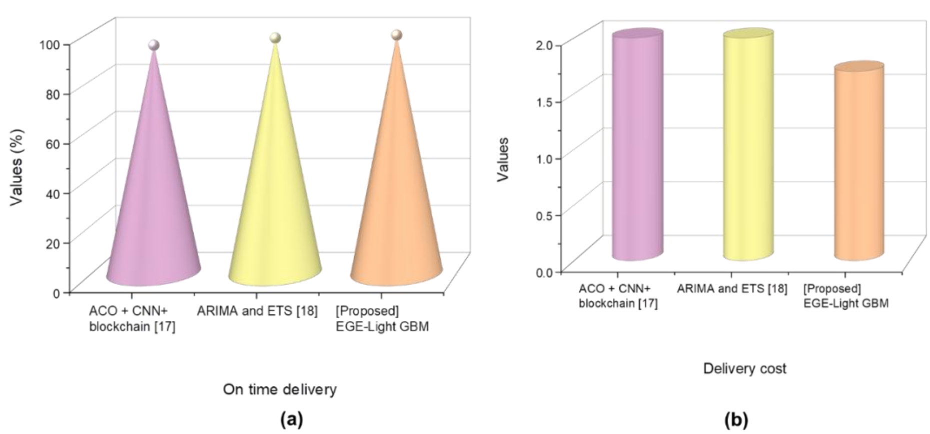

Figure 3 Comparison of delivery performance metrics: (a) delivery cost (b) on time delivery across different models

5 Discussions

The research is evident from the well-defined objective of enhancing transparency and decision-making in logistics. ARIMA and ETS [18] struggle with non-linear relationships and are poor in handling complex data. The methods are not well-suited for dynamic supply chain scenarios where real-time forecasting is crucial. ACO + CNN + block chain [17] although powerful in optimization, has significant computational costs and could be challenging to scale and integrate with other systems, thereby limiting their efficiency. The EGE-Light GBM model thus renders the following benefits: higher predictive accuracy, faster and better decision-making with less logistic operational costs while it optimizes route planning. In fact, with real-time data and advanced machine learning techniques, it reduces delivery costs with less carbon footprint and maximizes on-time delivery performances. It manages complicated issues better in supply chains than traditional methods.

6 Conclusion

This research aims at making the supply chain more transparent and enhancing the process of determining decisions with the help of IoT and AI. The dataset contained IoT device-gathered data in the form of RFID tags, GPS sensors, and environmental monitors for multiple stages of a supply chain. The preprocessing phase consisted of data cleaning, noise elimination, and the removal of duplicate entries. Min max normalization can used to normalize the data. EGE mutes the Light GBM model, which is used to predict risks, optimize routes, and improve transparency. It was observed that the model had a significant improvement over traditional methods in operational efficiency, risk prediction, and more accurate decision-making. The model performed well during the experiment; however, the major limitation is the quality of IoT data that dictates dependency. Future research areas can look into optimizing the adaptability of the model to diverse supply chain contexts and incorporating more advanced real-time analytics.

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