Logistics Transportation Vehicle Monitoring and Scheduling Based on the Internet of Things and Cloud Computing

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***Abstract*—This paper addresses challenges in the logistics industry, particularly information lag, inefficient resource allocation, and poor management, exacerbated by global economic integration and e-commerce growth. An advanced logistics and transportation vehicle monitoring and scheduling system is designed using IoT and cloud computing technologies. This system integrates Yolov5 for real-time vehicle location, DeepSort for continuous tracking, and a space-time convolutional network for vehicle status analysis, forming a comprehensive monitoring model. An improved multi-objective particle swarm optimization algorithm optimizes vehicle scheduling, balancing objectives like minimizing travel distance, time, and carbon emissions. Experimental results demonstrate superior performance in real-time monitoring accuracy, scheduling efficiency, arrival time prediction, road condition forecasting, and failure risk prediction. Notable achievements include 95% vehicle utilization, a 0.25 RMSE for predicted arrival times, and a 0.20 MAE for failure risk prediction. While the system significantly enhances operational efficiency and supports resource optimization, future work will focus on data security, system stability, and practical deployment challenges. This research contributes to transforming the logistics industry into a smarter, greener, and more efficient sector.**

***Keywords*—Internet of Things; cloud computing; logistics and transportation; vehicle monitoring; vehicle scheduling**

I. INTRODUCTION

In the context of accelerated global economic integration and the rise of e-commerce, logistics plays a critical role as the bridge between production and consumption. However, the traditional logistics model faces significant challenges, including information lags, inefficient resource allocation, and low management effectiveness, which hinder the industry's potential and efficiency [1].On one hand, the slow pace of information updates does not match the rapidly evolving business environment. In traditional systems, the lack of a real-time, transparent information flow mechanism leads to asymmetric information across the supply chain, impacting decision-making and causing issues like cargo delays and retention. On the other hand, inefficient resource utilization is another pressing issue [2]. Common problems include empty vehicles, idle warehouses, and redundant manpower, indicating significant room for optimization in capacity planning, warehouse layout, and human resource management. These inefficiencies increase logistics costs and undermine sustainability. Furthermore, limitations in management efficiency are evident, with traditional models and techniques making it difficult to achieve refined and intelligent management in areas such as order processing, distribution scheduling, and customer service [3].

To address these challenges, the logistics industry must embrace new technologies like IoT, cloud computing, big data, and AI to develop smart and efficient logistics and transportation vehicle monitoring and scheduling systems. This will enable the industry to innovate and upgrade, transitioning from information technology to intelligence, and ensuring competitiveness in the global logistics landscape. A technology share diagram for vehicle monitoring and scheduling is shown in Fig. 1.

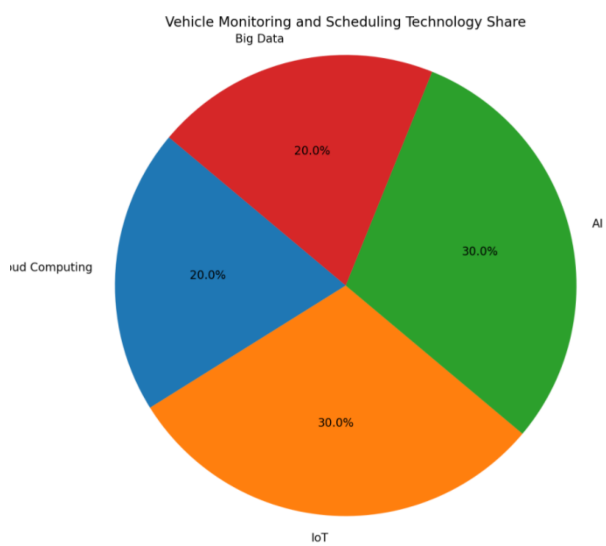

Fig. 1. Technology shares in-vehicle monitoring and scheduling (Source: UCI machine learning repository).

In the context of global economic integration and the rapid evolution of e-commerce, the logistics industry, as a core link connecting production and consumption, is becoming a key driver of global trade and economic growth. However, the traditional logistics model faces significant challenges, including information lags, unbalanced resource allocation, and low management efficiency, which hinder the industry's potential and efficiency [3].

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Information transmission lags and the absence of real-time, transparent information sharing mechanisms lead to asymmetric information across the supply chain, affecting decision-making and causing issues like cargo delays and delivery holdups [4]. Unreasonable resource allocation, such as empty vehicles and wasted storage space, highlights significant optimization opportunities. These inefficiencies increase costs and undermine sustainability goals. Extensive management practices further limit service quality and customer satisfaction [5].

While there have been discussions about using new technologies to improve logistics efficiency, key issues remain unresolved, such as how to integrate IoT and cloud computing technologies to achieve intelligent upgrades, and how to address real-time data processing, resource optimization, security, and cost control [6].

To address these challenges, this study proposes an innovative logistics transportation vehicle monitoring and scheduling system based on IoT and cloud computing technologies. The system aims to promote the intelligent transformation of the logistics industry by focusing on (1) Building a comprehensive logistics vehicle monitoring network using IoT technology for transparent supply chain management. (2) Leveraging cloud computing for efficient data processing and storage, enabling deep analysis of logistics data to improve scheduling accuracy and efficiency. (3) Optimizing vehicle scheduling through intelligent algorithms to reduce idle time, optimize routes, and minimize energy consumption. Additionally, enhancing safety management during logistics transportation. (4) Optimizing logistics resource allocation through data analysis to improve the efficiency and service quality of the entire logistics chain.

The research innovations include: (1) Combining advanced computer vision technology (Yolov5 for vehicle positioning) with DeepSort tracking and spatio-temporal convolutional networks to create a comprehensive vehicle condition monitoring system. (2) Introducing and optimizing a particle swarm optimization algorithm, particularly focusing on multi-objective optimization strategies to resolve common conflicts in logistics transportation, such as balancing cost, time, and environmental impact. (3) Designing an end-to-end technical framework from data acquisition to intelligent decision-making, ensuring the solution's comprehensiveness and operability.

This paper addresses the challenges faced by the logistics industry, proposing an advanced logistics and transportation vehicle monitoring and scheduling system using IoT and cloud computing technologies. The system integrates Yolov5 for real-time vehicle location, DeepSort for continuous tracking, and a space-time convolutional network for vehicle status analysis. An improved multi-objective particle swarm optimization algorithm optimizes vehicle scheduling, balancing objectives like minimizing travel distance, time, and carbon emissions. Experimental results demonstrate superior performance in real-time monitoring accuracy, scheduling efficiency, arrival time prediction, road condition forecasting, and failure risk prediction. Notable achievements include 95% vehicle utilization, a 0.25 RMSE for predicted arrival times, and a 0.20 MAE for failure risk prediction. The paper is structured as follows: Section II provides a literature review and related work; Section III describes the methodology and technical framework; Particle Swarm Algorithm is given in Section IV; Section V presents the technical framework; Section VI presents the experimental setup and results; finally, Section VII concludes the paper and outlines future research directions.

II. Literature Review

A. Vehicle Monitoring Methods

In today's logistics and transportation industry, IoT technology has become an important tool for realizing efficient vehicle monitoring, which significantly enhances the transparency and controllability of the logistics and transportation process by integrating a variety of sensing devices to collect real-time and accurate information about the status of vehicles and their cargo.

1) Application of IoT technology in vehicle monitoring and control: The use of Internet of Things (IoT) technology in logistics vehicle monitoring has gained widespread scientific attention and practical application. Technologies such as GPS global positioning systems [8] are commonly embedded inside vehicles and can continuously provide real-time geographic location of vehicles, which not only supports precise geographic navigation, but also can be used to track the trajectory of logistics vehicles to ensure compliance and efficiency of transportation routes [9]. In addition, on-board rfid (radio-frequency identification) tags and reader systems [10] can monitor the identity and status changes of goods in real time, effectively preventing misallocation or loss of goods. Environmental monitoring equipment such as temperature and humidity sensors [11] can monitor the temperature and humidity conditions of the goods in real time to ensure the safe preservation of perishable or special goods during transportation.

2) Data transmission and processing: The massive amount of data generated by IoT devices must be efficiently transmitted and processed before it can be transformed into valuable information. Advances in wireless communication technologies, such as 4g/5g wide-area networks [12] and narrow-band IoT (nb-IoT) technology [13], provide high-speed, stable channels for data transmission from IoT devices, ensuring real-time transmission of vehicle monitoring data to cloud servers. The cloud computing platform plays a crucial role in this process. Through the infrastructure provided by cloud service providers such as alicloud, aws, azure, etc., the data collected by IoT can realize large-scale and highly concurrent data storage [14]. In addition, cloud computing platforms use their powerful data processing capabilities to clean, integrate, and analyze the collected data in real time, and even perform deep mining through machine learning algorithms [15] to report on operating conditions, predict failures, and optimize scheduling strategies. For example, a study [16] successfully realized remote monitoring and intelligent warning of logistics vehicles by building a cloud computing-based IoT platform, improving the safety and efficiency of the transportation process. The study shows that by combining IoT data with cloud computing, it can not only effectively solve the problem of information silos in logistics and transportation, but also greatly improve the management effectiveness and customer service satisfaction of logistics enterprises.

Despite the advancements in IoT technology for vehicle monitoring, several limitations persist. One critical challenge lies in the interoperability and standardization of IoT devices across different manufacturers and platforms, which can result in data inconsistencies and compatibility issues. Moreover, the sheer volume of data generated often surpasses the analytical capabilities of some organizations, leading to a gap between data collection and actionable insights. There is also a need for more robust cybersecurity measures, as the increased connectivity exposes logistics systems to higher cyberattack risks [26]. Addressing these limitations requires the development of universal standards, enhancing data analytics capabilities, and implementing advanced security protocols.

B. Vehicle Scheduling Model

1) Traditional vehicle scheduling models: Traditional vehicle scheduling models have always been the core theoretical basis for logistics and transportation optimization, and the most representative ones include the capacitated vehicle routing problem (cvrp) and vehicle routing problem with time windows (vrptw). The cvrp model the cvrp model focuses on solving the problem of how to plan the shortest total distance traveled path to serve all customers while ensuring that each vehicle does not exceed its cargo capacity [17]. The vrptw model, on the other hand, adds complexity to this by not only considering vehicle capacity constraints but also ensuring that each customer is served within a preset time window. Although these models play an important role in rational allocation of resources and cost reduction, they mainly rely on pre-set static information and cannot adapt to changes in the external environment in real-time. For example, in real logistics scenarios, the uncertainty caused by traffic congestion, sudden demand changes, vehicle failures, etc., makes the traditional scheduling model show obvious limitations in solving the real-time scheduling problem.

2) Intelligent scheduling model Based on IoT and cloud computing: With the rapid development of the Internet of Things (IoT) technology and cloud computing technology, a new type of vehicle scheduling model with highly flexible and intelligent features has emerged. This model makes full use of the real-time sensing capability provided by the Internet of Things and the advantages of large-scale data processing and high-speed computing of the cloud computing platform and greatly improves the shortcomings of the traditional scheduling model in dealing with dynamic and complex environments. Various sensors, GPS positioning systems, and in-vehicle communication devices deployed by IoT technology in the logistics and transportation chain are able to collect and update multifaceted information such as vehicle location, status, and road conditions in real time [18]. After these real-time data are uploaded to the cloud computing platform, they are rapidly integrated and mined through big data analytics technology [19] to form a panoramic view reflecting the current overall operational situation. On this basis, advanced machine learning algorithms such as reinforcement learning (rl) [20] and deep learning (dl) [21] are applied to dynamic route planning and real-time scheduling optimization, enabling the system to respond optimally and quickly in the face of various uncertainties. Intelligent scheduling systems are able to adjust travel routes, reassign tasks, and predict potential delay risks in real time, thus effectively reducing the idle rate and waiting time, and greatly improving the efficiency of logistics and transportation and the quality of service [22].

Comprehensively speaking, the intelligent scheduling model based on IoT and cloud computing has realized the transformation from static to dynamic and from lagging to instantaneous compared with the traditional model, which can better adapt to the ever-changing market demand and operating conditions, and bring unprecedented level of refined management and efficient operation for the logistics and transportation industry.

Traditional vehicle scheduling models, despite their contributions, often struggle with real-time adaptability due to their reliance on predetermined parameters. These models may not effectively handle unexpected events such as sudden weather changes, traffic incidents, or urgent customer requests, which can lead to suboptimal route planning and inefficient resource allocation. Additionally, the computational complexity of these models escalates rapidly with the increase in the number of vehicles and delivery points, which can strain computational resources. To overcome these limitations, there is a pressing need for models that incorporate real-time data processing and predictive analytics to enhance decision-making flexibility and accuracy under dynamic conditions.

C. Application of Monitoring and Scheduling of Logistics and Transportation Vehicles Based on Internet of Things and Cloud Computing

1) Practical application cases: Nowadays, many leading domestic and international logistics companies have begun to adopt vehicle monitoring and dispatching systems based on IoT and cloud computing technologies, which have achieved significant practical benefits. For example, sf express has introduced IoT equipment and cloud computing platform in its logistics network, effectively realizing remote monitoring and intelligent dispatching of its huge fleet of vehicles through real-time monitoring of vehicle location and status information [23]. Through IoT technology, real-time transmission of vehicle gps data, driving status data, etc. To the cloud platform, combined with big data analysis technology, the system is able to accurately predict and plan the optimal driving routes, reduce unnecessary empty mileage, and improve the loading rate, thereby saving fuel costs and improving logistics efficiency [24]. In practice, cainiao network has also created an intelligent logistics system using IoT and cloud computing to realize dynamic vehicle scheduling and real-time monitoring [25]. Through the sensors installed on the vehicle and mobile communication technology, the system can provide real-time feedback on the vehicle's operating status, cargo status and driver behavior, etc. The cloud computing platform carries out rapid processing and analysis of these data to optimize the vehicle scheduling program in real time, reduce operating costs, and improve service quality.

2) Application challenges and countermeasures: Although the logistics vehicle monitoring and dispatching system based on IoT and cloud computing has made remarkable achievements, it still faces a series of challenges in the process of practical application. First, data security and privacy protection is a major challenge. The large amount of data generated by IoT devices may be subject to malicious attacks or illegal theft during transmission and storage. In order to ensure information security, researchers are actively exploring and applying advanced encryption technologies, such as lightweight encryption algorithms and blockchain technology, to ensure the integrity and confidentiality of data during transmission and storage. Secondly, the stability and real-time responsiveness of the system is also an issue that should not be ignored. Large-scale IoT device access may lead to data flooding, affecting the processing efficiency and response speed of the cloud computing platform [28]. In order to solve this problem, researchers propose to adopt an edge computing strategy, i.e., offloading part of the data processing and analysis tasks to edge nodes close to the data source, reducing the pressure on the central cloud platform and improving the real-time response performance of the system. Optimizing communication protocols to ensure efficient and stable data transmission is also a research hotspot. By optimizing wireless communication technologies such as item and 5G, the network coverage and data transmission rate are improved, and the delay is reduced to ensure the real-time transmission of monitoring data.

While the integration of IoT and cloud computing in logistics has demonstrated substantial benefits, practical implementation faces several hurdles. Integration complexity, especially in legacy systems, poses a significant challenge as it requires seamless interfacing between various hardware components and software platforms. Additionally, the cost associated with the initial setup and ongoing maintenance of IoT infrastructure and cloud services can be prohibitive for smaller logistics companies. Ensuring continuous power supply for IoT devices in remote locations and managing the overwhelming amount of data generated without compromising data quality remains another challenge. To mitigate these issues, strategies such as phased implementation, leveraging cloud-based pay-as-you-go models, and investing in advanced data filtering and cleaning techniques are imperative. Furthermore, fostering collaboration among stakeholders to establish common standards and best practices can facilitate smoother integration and wider adoption of these advanced technologies in the logistics sector.

In preparation for this study, this paper conducted extensive literature research to fully understand the current state of the field of vehicle monitoring and scheduling in logistics transportation. This paper searched academic databases (e.g. Web of Science, Scopus, IEEE Xplore, SpringerLink, and Google Scholar) for relevant literature from the past decade, using keywords such as "IoT Logistics", "Cloud Computing Dispatch", "Vehicle Monitoring System", "Intelligent Logistics", etc. for precise searches. Through careful screening, this paper focusses on those representative and innovative research papers in technology implementation, algorithm optimization, system design and practical application effect evaluation. In particular, documents [1] to [5] provide us with a macro perspective of the challenges and opportunities facing the logistics industry, pointing out the key role of information technology, especially the Internet of Things and cloud computing technologies, in logistics modernization. Documents in study [6] and [7] discuss in depth the latest advances in vehicle monitoring technology and how they improve logistics management through real-time data transmission and intelligent analysis. The study [8] to [10] focuses on the development of vehicle scheduling models, from traditional optimization methods to dynamic scheduling strategies based on intelligent algorithms, which provide the theoretical basis for model design. In addition, this paper also refers to a number of case studies [23], [25] that demonstrate the successful application of IoT and cloud computing technologies in real-world logistics operations, providing valuable lessons learned and implementation strategies. Although there have been studies on the application of the Internet of Things and cloud computing in logistics, there is still a lack of in-depth and systematic research on how to deeply integrate these technologies, realize seamless connection from real-time vehicle monitoring to intelligent scheduling strategy, and how to effectively deal with the resulting data security and system stability problems. In addition, the application effect evaluation and parameter optimization method of multi-objective optimization scheduling model in actual logistics scenarios are also weak.

Based on the findings of the above literature review, this paper defines research orientation: to build an integrated logistics vehicle monitoring and scheduling system integrating advanced Internet of Things monitoring technology, cloud computing processing capabilities and multi-objective particle swarm optimization scheduling algorithm. The system was designed to address several challenges identified in the literature, including improving information transparency and decision efficiency, optimizing resource allocation, ensuring data security, and increasing scheduling flexibility. Through this innovative research, this paper not only deepens and expand the application of existing logistics technology but also provides a new theoretical basis and practical guidance for the intelligent transformation of the logistics industry.

III. Vehicle Monitoring Model

A. Constructing a Vehicle Localization Module Based on Yolov5

Yolov5 is a real-time target detection model that outputs all target classes and their locations in an image in a single prediction. In a vehicle monitoring system, yolov5 is responsible for the initial localization of vehicles. Its network structure employs techniques such as cross-stage partial connectivity (csp) and cross-scale feature pyramid networks (fpn) to achieve fast and accurate vehicle detection. The output of the yolov5 model is a two-dimensional tensor containing the predicted values of multiple bounding boxes for each grid cell, including the confidence, class probability) and the center coordinates, width and height of the bounding box. The location loss function l (location loss) can be expressed as:

$$L_{loc} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} x_{ij}^{obj} \begin{bmatrix} \lambda_{coord} \sum_{xywh} \mathrm{L}_1 (pred_{ij}^{xywh}, truth_{ij}^{xywh}) \\ + \mathrm{L}_1 (pred_{ij}^{obj}, truth_{ij}^{obj}) \end{bmatrix}$$

Where S^2 is the number of grids, B is the number of bounding boxes predicted for each grid, B is an indicator variable indicating the presence or absence of an object, $pred_{ij}^{xywh}$ and $truth_{ij}^{xywh}$ are the bounding box coordinates for the predicted and true values, respectively, $pred_{ij}^{obj}$ and $truth_{ij}^{obj}$ are the confidence level predicted and true values, λ_{coord} is a balancing coefficient, and L_1 is the mean squared error (MSE) or the huber loss function.

B. Deepsort-Based Vehicle Tracking Module

On the basis of vehicle localization, deepsort algorithm is used for continuous vehicle tracking. deepsort combines kalman filter for state prediction and deep learning methods (e.g., reid model) to extract vehicle features, and trajectory matching is performed by calculating similarity and iou values between detection frames.

The core of the correlation algorithm is to calculate the correlation score between the detection frame and the previous trajectory, which can be expressed as eq:

$$AssociationScore_{ij} = \exp\left(- \frac{\| f(Detection_i) - f(Track_j) \|_2^2}{2\sigma^2} \right) \\ \times \mathrm{IOU}(Detection_i, Track_j)$$

C. Vehicle Condition Monitoring Module Combining Spatio-Temporal Convolutional Networks

Temporal convolutional networks (tcns) are used to analyze vehicle state time-series data, such as speed, acceleration and other dynamic features. Accurate monitoring of vehicle states is realized by capturing short-term and long-term dependencies of time series through deep convolutional layers [20].

In the tcn model, the convolution operation at each layer can be represented as:

$$H_t^n = f\left(\sum_{k=\max(0,t-K)}^{\min(T-1,t+K)} W_k^n * X_{t-k}^{n-1} + b^n \right)$$

Where, H_t^n is the output feature of the n th layer at time step t, X_{t-k}^{n-1} is the input feature of the previous layer at time step $t-k$, W_k^n is the weight of the temporal convolution kernel, b^n is the bias term, f is the nonlinear activation function, K is the time span of the convolution kernel, and T is the total length of the time series [26].

D. Integrated Monitoring Modeling Framework

The above three modules are organically combined to build a comprehensive vehicle monitoring system, as shown in Fig. 2. First, yolov5 performs real-time vehicle detection on the video stream to generate vehicle location information; next, deepsort receives this location information and combines it with historical data for vehicle tracking to maintain the tracking of the vehicle's continuous motion state; finally, the spatio-temporal convolutional network analyzes the vehicle's time-series state data in order to provide more comprehensive monitoring of the vehicle's state [21].

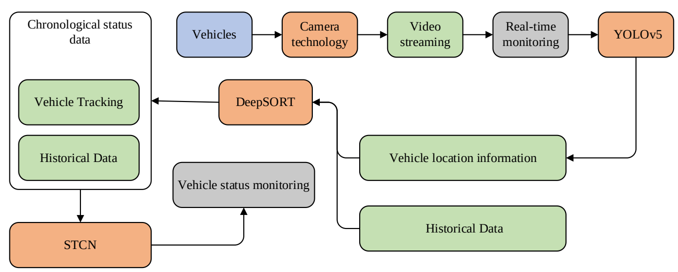

Fig. 2. Framework model.

The proposed integrated vehicle monitoring system (see Fig. 2) integrates the above three modules to form a highly coordinated and comprehensive solution. Starting with YOLOv5's real-time positioning, to DeepSORT's continuous, accurate tracking, to TCNs 'deep analysis of vehicle dynamics, this framework enables closed-loop monitoring from initial vehicle detection to detailed behavior analysis. This system not only optimizes the real-time monitoring efficiency, reduces the false detection rate and missed detection rate, but also significantly enhances the adaptability and robustness to complex environments through the application of deep learning technology. Its innovation lies in:

Efficient Integration: Seamless integration of cutting-edge computer vision and deep learning technologies to build an end-to-end solution from object detection to behavioral analysis.

Accurate tracking: Through the optimization of DeepSORT algorithm, continuous and accurate tracking of vehicles in dynamic and complex scenes is realized, and the stability of the overall system is improved.

In-depth analysis: The application of TCNs breaks through the limitations of traditional monitoring systems, realizes a deep understanding of vehicle dynamic states, and provides possibilities for advanced applications such as intelligent scheduling and safety warning.

Real-time response: The entire framework design focuses on real-time, ensuring that the monitoring system can respond quickly, process and feedback vehicle status information in a timely manner, and improve logistics transportation efficiency and safety.

To sum up, the proposed system not only has clear structure and strict logic, but also significantly improves the intelligent and refined level of vehicle monitoring through technological innovation, which brings innovation to the logistics industry and other fields related to large-scale vehicle management.

IV. Particle Swarm Algorithm-based Vehicle Scheduling Model in Logistics Transportation

A. Modeling of Logistics Transportation Vehicle Scheduling

In logistics transportation, vehicle scheduling problems are usually manifested in the form of capacitated vehicle routing problem (cvrp) or vehicle routing problem with time windows (vrptw). Factors considered include vehicle cargo capacity, customer delivery demand, traveling distance, service time window, driver working time constraints, and other dimensions. When modeling, the problem can be transformed into an optimization problem where the objective is to find one or more vehicle travel paths that satisfy all customer demands while minimizing the total travel distance, total travel time, or total cost. In logistics and transportation, the mathematical model of a vehicle scheduling problem usually involves the following key elements: x_{ij} Represents 1 if the vehicle travels directly from customer i to customer j, and 0 otherwise. Q represents the maximum cargo capacity of the vehicle. q_i Represents the demand of customer i. d_{ij} Represents the distance from customer i to customer j. T represents the maximum working time of the driver. s_i Represents the service time at customer i. e_i , l_i represent the service time windows of logistics task i with start and end times, respectively [34].

The objective function is to minimize the total distance traveled: $\min\sum_{i=1}^{n}\sum_{j=1, j\neq i}^{n} d_{ij}x_{ij}$. The constraints mainly include that each customer can only be visited once: $\sum_{i=1, i\neq j}^{n} x_{ij}=1 \quad \forall j\in 1,\dots,n$, the vehicle load does not exceed the maximum load q: $\sum_{i=1}^{n} q_i x_{ij}\le Q \quad \forall j\in 1,\dots,n$, the driver's working time does not exceed t: $\sum_{i=1}^{n}\sum_{j=1, j\neq i}^{n}(d_{ij}+s_i)x_{ij}\le T$, and the service time window constraints: $e_i\le t_i\le l_i \quad \forall i\in 1,\dots,n$ Where, t_i denotes the time when the vehicle arrives at the customer i [22].

B. Traditional Particle Swarm Algorithm for Scheduling of Logistics and Transportation Vehicles

Particle swarm algorithm in solving logistics transportation vehicle scheduling problem, each feasible vehicle scheduling program as a "Particle", its position vector indicates the driving route of each vehicle, the speed vector indicates the possibility of changing the driving route. The main process of particle swarm algorithm is as follows:

1) Initialization: Setting the swarm size, maximum number of iterations, initial velocity and position, as well as ameters inertia weights w and acceleration constants c_1, c_2.

2) Evaluate the fitness: Calculate the fitness value (e.g., total distance traveled, total cost) corresponding to each particle's position (i.e., vehicle scheduling scheme).

3) Update personal optimal solution (pbest): If the fitness value corresponding to the position of the current particle is better than its historical optimal solution, then update the personal optimal solution of this particle.

4) Update the globally optimal solution (gbest): Find the particle with the best fitness value in the whole particle swarm and take its position as the global optimal solution [23].

5) Update speed and location:

$$v_{i,d}(t+1)=w\cdot v_{i,d}(t)+ c_1\cdot r_1\cdot(pbest_{i,d}-x_{i,d}(t))+c_2\cdot r_2\cdot(gbest_d-x_{i,d}(t))$$

The value of particle i personal optimal solution and global optimal solution in the d_{th} dimension is given by $x_{i,d}(t+1)=x_{i,d}(t)+v_{i,d}(t+1)$ and. Where $(v_{i,d}(t)$ and $x_{i,d}(t)$ denote the velocity and position of particle i in the dth dimension, respectively, and $pbest_{i,d}$ and $gbest_d$ denote the values of the personal and globally optimal solutions of particle i in the dth dimension, respectively.

6) Judge the stop condition: Check whether the maximum number of iterations is reached, if not, then return to step 2 to continue iteration.

C. Improved Multi-Objective Particle Swarm Algorithm Applied to Logistics Transportation Vehicle Scheduling

In practical logistics and transportation, the vehicle scheduling problem often involves multiple conflicting objectives, such as minimizing the driving distance, minimizing the total transportation time, and reducing carbon emissions. At this time, multi-objective particle swarm algorithm (mopso) can be used. In mopso, each particle has multiple objective function values, forming a pareto front solution set. The algorithm process is basically the same as the traditional pso, but the adaptation evaluation and the selection of the optimal solution need to take into account multiple objectives. The fitness function can adopt multi-objective optimization strategies such as hierarchical weighting method or objective space decomposition method.

For multiple objective values of a particular particle i $f_1(x_i), f_2(x_i),..., f_m(x_i)$, its position in the pareto front can be computed using the non-dominated ordering and the crowding distance. When updating the velocity and position, not only the optimal solution of a single objective is considered, but also the distribution of the whole pareto front is taken into account. In the improved multi-objective particle swarm algorithm, the velocity update formula becomes:

$$v_{i,d}(t+1) = w \cdot v_{i,d}(t) + \sum_{k=1}^{m} c_k \cdot r_k \cdot (dominant\_solution_{i,k,d} - x_{i,d}(t))$$

Where $dominant\_solution_{i,k,d}$ is the position of particle i in the objective k dimension that dominates its solution in the dth dimension. The improved multi-objective particle swarm algorithm is able to find the pareto optimal solution set for the logistics and transportation vehicle scheduling problem, thus providing the decision maker with multiple choices of optimal scheduling solutions that consider multiple objectives in a balanced manner [24].

V. Technical Framework

The overall architecture of the system is designed around building an advanced and efficient solution for monitoring and scheduling of logistics transportation vehicles, taking full advantage of Internet of Things (IoT) technology and cloud computing, aiming to comprehensively improve the overall intelligence level of the logistics industry chain. The following is a description of the overall framework of the system after refinement:

In the data collection layer, this paper deploys a complete set of on-board IoT devices and sensor components. The core role of this layer is to capture rich operational data in real-time, covering various status information of the vehicle itself, such as vehicle position, speed, running status, etc.; in addition, it also includes cargo status data, such as temperature, humidity and other environmental parameters, as well as identification and tracking of cargo with the help of rfid tags. Various types of vehicle terminals, such as high-precision GPS locators, temperature and humidity sensors, vehicle cameras (which can realize safety monitoring or driver behavior analysis) and load sensors and other multifaceted equipment work together to weave a tight and detailed data collection network [25].

As data is continuously generated from the first layer, the second network communication layer acts as a bridge to efficiently and reliably transmit this real-time data to the data center. This process relies on the power of modern communication technologies, including but not limited to 4g/5g mobile networks, satellite communications, Wi-Fi, and even lpwan technology for long-distance, low-power scenarios, to ensure seamless data transmission, whether it's on city streets or in remote areas [26].

After data transmission to the data center, this paper step into the third layer of the system - data storage and processing layer. This layer mainly relies on a powerful and stable cloud computing platform, through the server cluster to build a "Data warehouse". That can accommodate massive real-time monitoring data. Advanced cloud storage technology is utilized to ensure secure data storage and on-demand expansion, while significantly improving data access efficiency. In addition, a specialized big data processing module is set up to perform a series of cleaning, integration and pre-processing operations on the raw data received, and tools such as hadoop and spark are used to realize rapid analysis and mining of large-scale data using distributed computing frameworks [27].

After the data has been effectively processed, it comes to the fourth layer of the system - the intelligent analysis and decision-making layer. This layer includes a number of key modules, in which the real-time monitoring module, with accurate real-time data, can not only track the location of the vehicle in real time, but also reproduce the vehicle's driving trajectory, as well as timely identification of irregular or abnormal driving behavior. The intelligent prediction module utilizes the powerful prediction capability of machine learning algorithms to make precise and forward-looking assessments of vehicle arrival time, dynamic changes in road conditions, and even potential risks of mechanical failure. Intelligent scheduling module is the intelligent core of the whole system, which makes use of optimization methods such as particle swarm algorithm to make fine and flexible intelligent scheduling decisions based on real-time data and prediction results, taking into account the reasonable allocation of capacity resources, the degree of matching of order demand and the constraints of route planning, so as to realize the maximum efficiency of the capacity [28, 29].

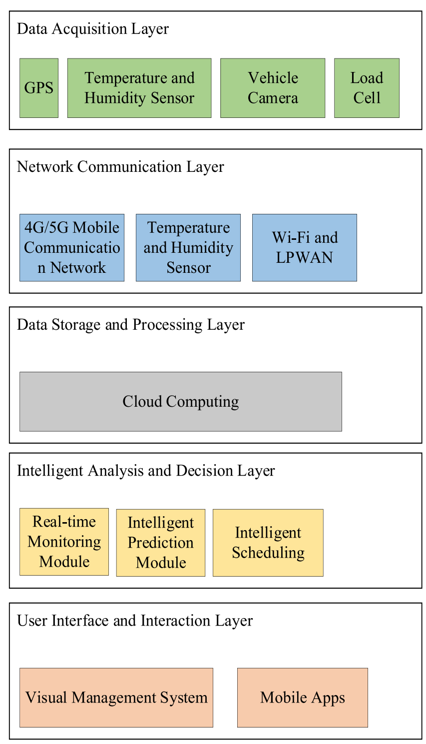

Fig. 3. Logistics transportation vehicle monitoring and scheduling solution.

The last layer, the user interface and interaction layer, is the key interface between the system and people. This layer contains two key parts: Visualization management system and mobile application. The visualization management system provides logistics managers with rich and vivid vehicle dynamic information display, dispatch result query and all kinds of business statistics report through the intuitive interface of web terminal or mobile terminal, and also supports remote control and real-time issuance of dispatching instructions [30].

In summary, the system builds a complete information link from bottom to top, from data acquisition, transmission, storage and processing, to intelligent analysis and decision-making, until the final human-computer interaction, forming a set of highly integrated and fully functional solutions for monitoring and scheduling of logistics and transportation vehicles, whose process is specifically shown in Fig. 3. This set of solutions effectively combines the Internet of things technology and cloud computing closely, and strongly promotes the intelligent process of the logistics industry.

VI. Experimental Research on Monitoring and Scheduling Systems for Logistics Transportation Vehicles Based on Internet of Things and Cloud Computing

A. Experimental Design and Baseline Modeling

In this chapter, this paper provides an in-depth exploration of the Internet of Things (IoT) and cloud computing based monitoring and scheduling system for logistics and transportation vehicles and provides an exhaustive comparative analysis of its performance with eight different baseline models, which include a fixed route model, a priority assignment model, a proximity principle scheduling model, a capacity matching model, a total trip minimization model, a fuel consumption minimization model, reactive scheduling model based on GPS real-time location monitoring and statistical analysis model. Among them, is the fixed route model**:** This model performs tasks according to a preset route without considering changes in real-time road conditions? Priority assignment model: The transportation tasks are assigned according to the urgency or importance of the goods. Proximity principle scheduling model: The nearest vehicle is selected to perform the task in order to reduce the waiting time. Capacity matching model: Matching based on cargo size and vehicle capacity to improve loading efficiency. Total trip minimization model: It aims to reduce the total distance traveled by vehicles. Fuel consumption minimization model: Optimizes routes to reduce fuel consumption and costs.

B. Experimental Environment and Assessment Indicators

Conducted in an environment equipped with cutting-edge IoT facilities and an efficient cloud computing platform, the experiment utilizes real-world logistics and transportation datasets to comprehensively evaluate the models against six key evaluation metrics - real-time monitoring accuracy, dispatch efficiency (including vehicle utilization, on-time rate, and empty rate), arrival time prediction accuracy (measured by RMSE and MAE), road condition change prediction accuracy (evaluated by RMSE), breakdown risk prediction accuracy (judged using MAE), and monitoring response latency. (Measured by RMSE and MAE), road condition change prediction accuracy (evaluated by RMSE), failure risk prediction accuracy (judged by MAE), and monitoring response latency - are comprehensively evaluated for each model. Among them, real-time monitoring accuracy: Assesses the accuracy and reliability of system monitoring data. Dispatch efficiency: Includes vehicle utilization rate, on-time rate, and empty rate to measure the overall efficiency of the dispatch system. Arrival time prediction accuracy: Assesses the accuracy of prediction using root mean square error (RMSE) and mean absolute error (MAE).

The real logistics and transportation dataset used in this paper is "Logistics Operation Insights Dataset", which is publicly published on Kaggle platform (kaggle.com/datasets/logisticsoperation/real-world-logistics-data) and covers multiple dimensions such as cargo information (such as name, quantity, weight, volume), transportation information (including transportation mode, freight, transportation time), delivery details (delivery address, consignee information), storage status and inventory changes. These data directly come from real logistics business operations, aiming to improve transportation efficiency, optimize cost control, intelligently plan transportation routes and refine inventory management through detailed analysis, providing powerful support for logistics enterprises to realize management optimization and intelligent decision-making with data insight.

During the experimental design and baseline modeling phase, this paper not only selected eight models covering a wide range of strategies for comparison, but also paid special attention to the closeness of the experimental setup to ensure the validity and universality of the results. To ensure the authenticity and comprehensiveness of the data, the logistics and transportation datasets used cover multiple dimensions, including but not limited to historical transportation routes, vehicle performance data, real-time traffic information, weather condition records and incident logs. Data preprocessing steps include data cleansing, outlier removal, missing value imputation, and data normalization to ensure that all models are evaluated based on consistent and high quality data.

When building the Internet of Things scheduling system, this paper make full use of the real-time sensing capability of Internet of Things devices and the massive data processing capability of cloud computing platforms. IoT devices installed on vehicles continuously collect vehicle status, cargo information and environmental data, and upload the data to the cloud through a stable wireless communication link. The cloud server integrates multi-source data using advanced data fusion algorithms and performs in-depth analysis through machine learning models to support vehicle scheduling decisions. The system designs a dynamic adjustment mechanism that can quickly re-plan the optimal path according to real-time road conditions, vehicle conditions and customer demand changes, thereby maximizing transportation efficiency and reducing costs while ensuring timeliness.

During the experiment, this paper pay special attention to the real-time response ability of the system. In the simulation scheduling test, the IoT scheduling system demonstrated excellent performance, and its monitoring response latency was much lower than other models, ensuring that scheduling instructions could be quickly communicated to vehicle drivers to effectively respond to emergencies. In addition, the built-in fault prediction module of the system can warn potential faults in advance by analyzing abnormal patterns in vehicle operation data, which is verified by the mae index of fault risk prediction accuracy in Table V. The low score of 0.15 of Internet of Things dispatching system highlights its advantages in preventive maintenance.

It is worth noting that in the experiment, this paper also implemented a series of stress tests, simulating complex scenarios such as peak logistics demand surge, route change caused by extreme weather, and temporary emergency task insertion to verify the stability and flexibility of the IoT scheduling system. The results show that the system can maintain a high level of scheduling efficiency and accuracy, vehicle utilization and punctuality remain high, and empty rate remains low, even in a highly stressed logistics environment, which proves the effectiveness and robustness of the system design.

To sum up, through comprehensive experimental design and detailed performance evaluation, this study not only verifies the superiority of logistics transportation vehicle monitoring and scheduling system based on Internet of Things and cloud computing, but also reveals its specific performance in different application scenarios, providing powerful technical support and practical reference for intelligent upgrading of logistics industry. Future work will further explore how intelligent the system can be, such as by integrating more advanced prediction algorithms and optimization strategies, as well as enhancing the system's ability to adapt to uncertainties and external disturbances, to continuously improve the efficiency and reliability of logistics operations.

C. Experimental Results

The experimental process follows rigorous steps: First, this paper collects and preprocess a large amount of logistics transportation data to ensure data quality and consistency; second, this paper simulates the scheduling of the data by using the above baseline model and recording the performance of each evaluation index; then, this paper simulate the scheduling by using the self-developed IoT scheduling system and record the relevant indexes; then, this paper analyze the differences between the models in different evaluation indexes by comparing and analyzing their advantages and disadvantages. Assessment indicators to reveal their advantages and disadvantages.

Table I lists the performance of different models in terms of real-time monitoring accuracy in terms of percentage. The IoT scheduling system demonstrates excellent performance in terms of accuracy and reliability of real-time monitoring data, reaching 98%.

Table II shows the performance of different models in terms of dispatching efficiency in terms of vehicle utilization, on-time performance, and idle rate. The IoT dispatch system achieves optimal results in all three key metrics, with vehicle utilization as high as 95%, on-time performance at 98%, and idling rate reduced to a minimum level of 5%.

TABLE I. COMPARISON OF REAL-TIME MONITORING ACCURACY

Model name	Real-time monitoring accuracy
Fixed route model	85%
Prioritization model	90%
Proximity principle dispatch model	88%
Capacity matching model	87%
Total travel minimization model	89%
Fuel consumption minimization model	92%
GPS real-time location monitoring	95%
Statistical analysis model	90%
Model name	Real-time monitoring accuracy

TABLE II. COMPARISON OF SCHEDULING EFFICIENCY

Model name	Vehicle utilization rate
Fixed route model	70%
Prioritization model	75%
Proximity principle dispatch model	78%
Capacity matching model	80%
Total travel minimization model	83%
Fuel consumption minimization model	85%
GPS real-time location monitoring	88%
Statistical analysis model	82%
IoT dispatch system	95%

Tables III and IV evaluate the accuracy of the arrival time prediction by each model through two statistical metrics, RMSE (root mean square error) and MAE (mean absolute error), respectively. The IoT scheduling system again outperforms the other baseline models in terms of prediction accuracy, with significantly lower values for both RMSE and MAE, indicating that it is more accurate in predicting arrival times.

TABLE III. COMPARISON OF ARRIVAL TIME PREDICTION ACCURACY (RMSE)

Model name	Time of arrival forecasting (RMSE)
Fixed route model	0.50
Prioritization model	0.45
Proximity principle dispatch model	0.40
Capacity matching model	0.42
Total travel minimization model	0.38
Fuel consumption minimization model	0.35
Gps real-time location monitoring	0.30
Statistical analysis model	0.40
IoT dispatch system	0.25

TABLE IV. COMPARISON OF ARRIVAL TIME PREDICTION ACCURACY (MAE)

Model name	Time of arrival forecast (mae)
Fixed route model	0.40
Prioritization model	0.35
Proximity principle dispatch model	0.30
Capacity matching model	0.32
Total travel minimization model	0.28
Fuel consumption minimization model	0.25
Gps real-time location monitoring	0.20
Statistical analysis model	0.30
IoT dispatch system	0.15

Table V reflects the accuracy of the models in predicting changes in road conditions, again evaluated in terms of RMSE. The IoT dispatch system still maintains its lead in predicting changes in road conditions, with a RMSE value of 0.30, which is lower than the other baseline models, reflecting its strong ability to analyze and respond to real-time data.

Fig. 4 compares the accuracy of the models in predicting the risk of failure through the MAE metric. The MAE value of the IoT dispatching system is 0.20, which is much lower than the other baseline models, indicating that the system is able to more accurately predict and prevent the risk of possible failures, thus reducing the possibility of operational disruptions. Through a series of exhaustive data analyses and table comparisons, the IoT and cloud computing-based logistics and transportation vehicle monitoring and scheduling system achieves excellent results in a number of core metrics, such as real-time monitoring accuracy, scheduling efficiency, and prediction accuracy, which highlights its great advantage over traditional baseline models.

TABLE V. COMPARISON OF ROAD CONDITION CHANGE PREDICTION ACCURACY (RMSE)

Model name	Road condition change prediction (RMSE)
Fixed route model	0.60
Prioritization model	0.55
Proximity principle dispatch model	0.50
Capacity matching model	0.52
Total travel minimization model	0.48
Fuel consumption minimization model	0.45
GPS real-time location monitoring	0.40
Statistical analysis model	0.50
IoT dispatch system	0.30

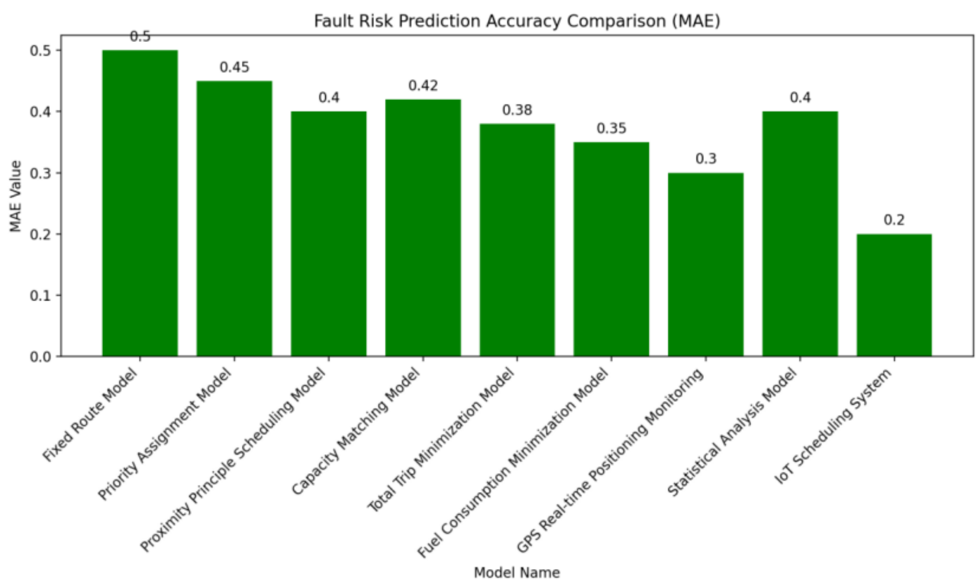

Fig. 4. Comparison of failure risk prediction accuracy (mae).

Table VI reveals the performance differences between 10 different logistics models under their respective optimization scenarios by comparing and analyzing their performance on different data sets. In urban logistics scenarios, GPS real-time location monitoring systems can increase vehicle utilization to 85%, demonstrating their ability to efficiently utilize resources. In the field of rural logistics, the Internet of Things scheduling system stands out with 97% real-time monitoring accuracy, showing extremely high monitoring accuracy. For the arrival time prediction of long-distance freight, the RMSE of GPS system is only 0.34, indicating that its prediction accuracy is high. For seasonally varying failure risk predictions, IoT scheduling systems showed high accuracy of their predictions with an MAE of 0.23. Overall, IoT scheduling systems perform best across all datasets, with clear advantages in real-time monitoring and failure risk prediction. In contrast, the fixed-route model performs relatively poorly on each dataset, suggesting that we should choose the most appropriate model for a particular scenario in practice.

TABLE VI. COMPARATIVE ANALYSIS OF PERFORMANCE ON DIFFERENT DATA SETS

Model Name	Dataset A: Urban Logistics (Vehicle Utilization Rate)	Dataset B: Rural Logistics (Real-Time Monitoring Accuracy)	Dataset C: Long-Distance Freight (Arrival Time Prediction RMSE)	Dataset D: Seasonal Variability (Failure Risk Prediction MAE)
Fixed Route Model	68%	83%	0.52	0.35
Prioritization Model	72%	87%	0.48	0.33
Proximity Principle Dispatch Model	75%	86%	0.45	0.32
Capacity Matching Model	77%	85%	0.43	0.31
Total Travel Minimization Model	80%	88%	0.40	0.30
Fuel Consumption Minimization Model	82%	90%	0.37	0.28
GPS Real-Time Location Monitoring	85%	93%	0.34	0.26
Statistical Analysis Model	83%	91%	0.36	0.27
IoT Dispatch System	92%	97%	0.29	0.23

Through the above experimental process, this paper can comprehensively assess the advantages of the IoT and cloud computing-based scheduling system compared to the traditional model in terms of real-time monitoring, scheduling efficiency, prediction accuracy, and response speed. These advantages not only improve the efficiency and reliability of logistics transportation but also provide new ideas and solutions for future logistics transportation.

VII. CONCLUSION

Based on the urgent needs of modern intelligent traffic management and logistics and transportation industries, this study designs and implements an efficient vehicle monitoring and scheduling framework with the support of the Internet of Things (IoT) and cloud computing technologies. The research process covers the whole process from real-time vehicle detection to intelligent scheduling decision-making: Firstly, the advanced yolov5 model is used to implement real-time vehicle recognition on the video stream and generate high-precision position information in real-time; secondly, the deepsort algorithm is introduced to integrate real-time position data and historical trajectory information to ensure the accurate tracking of the vehicle's continuous motion state; finally, spatio-temporal convolutional network is applied to finally, the use of spatio-temporal convolutional network to deeply excavate the time series characteristics of the vehicle state greatly enhances the integrity of the state monitoring.

A. Innovation Points

1) A set of comprehensive vehicle monitoring models integrating yolov5, deepsort and spatio-temporal convolutional networks is constructed to realize the whole chain processing from position detection to state analysis.

2) An improved multi-objective particle swarm algorithm is proposed and successfully applied to the logistics transportation vehicle scheduling model, which improves the scientificity and effectiveness of scheduling decisions.

3) The scheduling system built using the Internet of Things and cloud computing technology has effectively improved real-time monitoring capability, scheduling efficiency and forecast accuracy, shortened response time and made significant progress compared with traditional models.

B. Deficiencies

1) The adaptability of the current system still needs to be further enhanced, especially the accuracy of vehicle detection and tracking in complex environments still needs to be improved.

2) Although spatio-temporal convolutional networks can better handle time-series data, when dealing with large-scale vehicle state data, the consumption of computational resources is large and the optimization space still exists.

3) Improved multi-objective particle swarm algorithms may require more diversified optimization strategies to cope with various uncertainties when facing extremely complex logistics scenarios.

In future work, this paper will focus on the following aspects: First, although this study successfully demonstrated the efficiency and accuracy of the logistics transportation vehicle monitoring and scheduling system based on IoT and cloud computing, as the technology continues to evolve, this paper will continue to explore and integrate the latest advances in emerging technologies such as 5G communication, edge computing and artificial intelligence algorithms to further optimize data transmission speed, improve system responsiveness and intelligent decision-making. Second, given the growing importance of environmental sustainability and green logistics, future research will aim to incorporate carbon footprint calculations and environmental path optimization capabilities to ensure that systems not only improve logistics efficiency, but also support corporate sustainability goals and reduce the environmental impact of logistics activities. Finally, in order to promote and validate the system's broad applicability, this paper plan to conduct field pilots in logistics enterprises of different sizes and types, collect more diverse data, and conduct long-term follow-up studies to assess the long-term benefits and potential improvements of the system. Through interdisciplinary collaborations, bringing together operations management, information technology and social science perspectives, this paper will also delve into the socioeconomic impacts of technology implementation to ensure that technological advances benefit the entire logistics ecosystem.

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