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Deep Learning-Enhanced Proactive Strategy: LSTM and VRP/ACO for Autonomous Replenishment and Demand Forecasting in Shared Logistics

Martin Straka and Kristína Kleinová *

Institute of Logistics and Transport, Technical University of Kosice, 042 00 Kosice, Slovakia; martin.straka@tuke.sk
* Correspondence: kristina.kleinova@tuke.sk

Abstract

At present, the global logistics sector faces critical challenges, including rising energy costs and pressure to reduce CO_2 emissions. Traditional linear supply chains are becoming inefficient, necessitating a transition toward shared logistics based on the principles of the sharing economy. This paper presents a progressive three-layer architecture that transforms conventional reactive data collection into an autonomous, proactive management system for the distribution of consumable materials. While previous research established foundations in IoT connectivity for smart vending machines, this study advances the process by integrating an intelligent layer of artificial intelligence (AI) algorithms. The framework utilizes Long Short-Term Memory (LSTM) neural networks for demand forecasting, dynamic route optimization (VRP/ACO) for replenishment, and Isolation Forest/DBSCAN algorithms for real-time anomaly detection. To evaluate the framework, a numerical simulation was conducted using representative pilot scenarios. The results indicate that within the simulated environment, the system achieves over 95% accuracy in inventory depletion prediction (MAPE = 4.02%). In these analyzed instances, this leads to a 25–30% reduction in stock-out risks and a 25% reduction in replenishment distance. These findings demonstrate the significant potential for reducing operational costs and carbon footprints in green logistics. The study confirms that the synergy between IoT infrastructure and AI-driven analysis provides a robust foundation for transitioning from static methodologies to resilient, collaborative logistics ecosystems.

Keywords: shared logistics; Internet of Things (IoT); artificial intelligence

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1. Introduction

At present, the global logistics sector is facing challenges such as rising energy costs, labor shortages, and pressure to reduce CO_2 emissions. Traditional models of linear supply chains are becoming inefficient. In this context, shared logistics, built on the principles of the sharing economy, appears to be an essential paradigm for increasing the efficiency of resource utilization. The sharing economy represents a complex system based on the collective use of resources and services among individuals or organizations in order to maximize their utilization rate and minimize losses [1].

From an economic perspective, this model is closely linked to the principles of the circular economy, where the repeated use of assets contributes to higher economic efficiency and waste elimination [2]. From a technological perspective, this system is conditioned by digital infrastructure that enables efficient real-time matching of supply and demand.

Environmental sustainability in this context is achieved through the reduction in primary raw material consumption, while principles of social justice ensure more equitable access to goods for disadvantaged groups. The application of collaborative design and innovative approaches within the sharing economy enables the creation of sustainable solutions that harmonize economic growth with social responsibility [3]. It is precisely this multidisciplinary nature of the sharing economy that forms the essential theoretical basis for understanding the concept of shared logistics in the era of digitalization.

The sharing economy is defined by various scholars as a technologically supported socio-economic platform that enables the sharing of underutilized assets among a network of participants [4]. Some research describes it as a platform-based model facilitating peer-to-peer exchange or the rental of resources, particularly in the context of accommodation among private individuals [5]. Furthermore, it is understood as an economic system where consumption and production occur through sharing, renting, or the repeated use of assets rather than through ownership [6]. Ultimately, the sharing economy represents an ecosystem of digital platforms connecting providers and users to efficiently utilize existing resources [7].

While the sharing economy provides a broader theoretical and socio-economic framework for the transition from ownership to shared use of assets, shared logistics transforms this concept into specific operational processes. In practical terms, this means that companies cease to perceive logistics infrastructure, such as warehouses or transport vehicles, as exclusively private resources and instead approach them as shared capacities within a collaborative network [1]. The synergy between these areas creates space for technological innovation, where digital platforms serve as intermediaries for the dynamic allocation of resources in real time. Within the context of digitalization, shared logistics makes use of IoT. IoT can be defined as a digital infrastructure that enables physical logistics assets to become part of an intelligent information network.

IoT represents critical infrastructure for the transition of shared logistics from the theoretical level to practice, as through real-time monitoring it ensures transparency among partners, eliminates errors in manual records, and enables an immediate system response to dynamic changes in the distribution network. It is a network of physical objects, vehicles, devices, and other "things" equipped with sensors, software, and network connectivity that allow these objects to collect and share data without direct human interaction. According to them, IoT is part of applications including supply chain and logistics systems, where sensors and real-time communication support the monitoring, processing, and analysis of logistics processes (e.g., inventory tracking, transportation, environmental conditions) [8]. Technologies such as IoT, GPS, automatic identification, and digital platforms are considered "fundamental" for the operation of electronic platforms for shared logistics, as they enable real-time tracking, monitoring, and information sharing among logistics actors [9].

Shared logistics currently represents a key paradigm in the field of supply chain management, enabling companies to collaboratively utilize transport capacities, warehouse space, and information infrastructure. This approach, classified within hierarchical levels from 1PL to advanced 6PL models, effectively transcends the boundaries of individual companies and creates integrated collaborative ecosystems [3,10]. The physical layer of these systems is formed by intelligent contact points, primarily smart parcel lockers and autonomous warehouse units, which serve as critical nodes for ensuring the smooth flow of goods in a shared environment.

Despite the existence of robust theoretical frameworks, such as expert decision matrices for strategic planning [3], current approaches in practice exhibit a significant degree of rigidity. The main scientific problem remains the static nature of these methodologies, which are unable to reflect dynamic changes in supply and demand in real time [11]. This

technological gap, arising from the separation of logistics methodology from its technical implementation, leads to suboptimal utilization of shared resources and limits the overall agility of the system.

A solution to this issue is the integration of IoT and artificial intelligence (AI), which form the technological core of Logistics 4.0 [12]. The implementation of IoT sensors in logistics automation systems and transport vehicles enables continuous data acquisition on occupancy and inventory status [13]. Subsequent processing of these data using AI algorithms enables the automation of decision-making processes that were previously dependent on manual input, thereby achieving autonomous route optimization and dynamic selection of the appropriate level of sharing. This transition from "paper-based decision-making" to intelligent real-time management is a necessary step toward increasing efficiency in the modern industrial environment [13,14].

The objective of the presented article is therefore to propose a comprehensive framework that integrates shared logistics decision-making methodology with advanced AI and IoT technologies. The work builds on previous research in the field of logistics matrices and the possibilities of integrating IoT into distribution logistics [15] and extends them with an intelligent systems layer.

The scientific novelty of this study, which distinguishes it from our previous research, lies in the transition from a passive IoT monitoring framework to a class of autonomous AIoT utilization. Unlike earlier models that focused on data acquisition from individual vending nodes, this paper formalizes a unified multi-module optimization architecture. Its primary contribution is the integration of predictive forecasting and dynamic route planning within a shared-resource environment, establishing a new methodology for cross-enterprise logistics coordination that was absent in earlier IoT-centric frameworks.

Academic literature highlights that digital platforms and data-centric coordination are vital for cutting costs and risks in shared-resource environments [16]. Initial studies in this field primarily addressed connectivity and the monitoring of physical states [3]. However, current Industry 4.0 trends shift the focus toward intelligent analysis to drive business value.

Academic literature highlights that digital platforms and data-centric coordination are vital for cutting costs and risks in shared-resource environments [16]. Initial studies in this field primarily addressed connectivity and the monitoring of physical states [3], but current Industry 4.0 trends shift the focus toward intelligent analysis to drive business value. While Zhong et al. [17] built a broad framework for Industry 4.0, their model centers on internal production synchronization. This research expands that scope by tackling the decentralized and stochastic nature of shared logistics through targeted AI layers.

The utility of LSTM networks for industrial forecasting was validated by Sagheer and Kotb [18], and further evidence from Kanwal et al. [19] shows that high-precision replenishment forecasts increase supply chain resilience against production fluctuations. These predictive capabilities are closely linked to collaborative route planning, which is a recognized driver of logistics efficiency [20]. Recent AI-based Vehicle Routing Problem (VRP) studies show operating cost cuts between 18% and 22% [21,22], along with notable fuel savings [23,24].

Furthermore, combining adaptive routing with anomaly detection is essential to limit inefficiencies at distribution nodes [25]. Industrial applications of similar algorithms report savings from 18% to 25% in demand-driven logistics [26,27]. By integrating these components, this paper proposes a unified methodology that moves beyond isolated AI applications toward a coordinated AIoT system.

1.1. Related Work on AI-Enabled Smart Logistics

The proposed framework aligns with the broader megatrend of AI-driven process digitalization within logistics and industrial systems. As highlighted in recent studies on the digital transformation of industrial processes [28], the integration of autonomous intelligence is no longer an isolated enhancement but a fundamental shift in managing complex supply chain trajectories.

The transition toward autonomous logistics necessitates the integration of several fields of AI. Current research in this sphere focuses on three primary pillars: demand forecasting, route optimization, and system reliability through anomaly detection.

Industrial demand forecasting increasingly centers on deep learning, specifically the utilization of LSTM networks. The LSTM model uses a standard sequential architecture with ReLU activation to ensure efficient demand forecasting. As validated by Sagheer and Kotb [18], LSTM models outperform traditional statistical methods in capturing the non-linear and stochastic nature of industrial consumption. In vending machine networks and smart warehouses, high-precision forecasting is essential to ensure supply chain resilience against production fluctuations [19].

In terms of transport efficiency, VRP and Ant Colony Optimization (ACO) are widely applied to optimize replenishment cycles for locker and vending systems. Collaborative planning within these networks is vital for maintaining logistics efficiency [20]. Recent studies documenting AI-driven VRP implementations report reductions in operating costs ranging from 18% to 22% [21,22], highlighting the economic efficiency of dynamic routing within decentralized distribution systems.

The third pillar, anomaly detection in logistics-oriented IoT systems, serves to ensure data integrity. The implementation of adaptive filters and anomaly detection layers is necessary to limit inefficiencies caused by sensor malfunctions or unauthorized material withdrawals [25]. While these components are often studied in isolation, a clear research gap exists in their practical integration. Most existing frameworks treat forecasting, routing, and anomaly detection as separate processes, whereas our proposed methodology fuses them into a single, coordinated AIoT system designed for multi-tenant shared logistics.

1.2. Research Gap and Contribution

While existing research has explored IoT and AI in isolation, a significant gap remains in the integration of these technologies into a unified autonomous framework for multi-tenant shared logistics. This article addresses this gap through the following contributions [23,29]:

a. **Beyond Previous Work:** Unlike earlier research that focused primarily on the connectivity and data acquisition layers of IoT nodes, this study proposes a proactive coordination logic that enables autonomous decision-making across the logistics network as a whole.
b. **Advancing AIoT for Smart Logistics:** In contrast to standard IoT + AI applications that often treat individual modules as isolated enhancements, this framework ensures that anomaly detection, demand forecasting, and route optimization operate within a synergistic feedback loop.
c. **Enhanced LSTM Application:** While the literature on LSTM-based forecasting typically focuses on single-enterprise supply chains, this work adapts LSTM networks for a multi-enterprise shared-resource environment.
d. **Resource Pooling Framework:** This paper provides a formalized treatment of sharing economy mechanisms—such as load consolidation and partial cost allocation—which are frequently absent in purely technical IoT frameworks.

2. Materials and Methods

To ensure the seamless integration of AI techniques within the shared logistics framework, it is essential to establish a clear mapping between operational challenges and the proposed technological solutions. Shared logistics systems, particularly those utilizing automated vending nodes, encounter four fundamental bottlenecks.

First, demand volatility at vending nodes creates fluctuations that lead to either stock-outs or excessive inventory levels (Table 1). We address this issue through LSTM networks, which transform the system from a reactive to a predictive replenishment model. Second, transportation batching constraints and suboptimal route planning increase operational costs. Our TSP optimization module recalculates delivery paths to minimize transportation distance. Third, the information asymmetry between the physical state of inventory and the digital record (caused, for example, by material losses or sensor errors) is addressed by the anomaly detection module. Finally, high coordination costs are reduced by the integrated AIoT Cloud architecture, which automates decision-making processes.

Table 1. Problem–Solution Mapping in Shared Logistics AI Framework.

Logistics Challenge	Operational Point	Proposed AI Module	Primary Benefit
Demand Volatility	Stock-outs or overstocking at vending nodes.	LSTM Forecasting	Predictive replenishment & inventory optimization.
Logistics Inefficiency	Suboptimal routing and high transportation costs.	TSP Optimization	Reduced driven kilometers & fuel consumption.
Information Asymmetry	Undetected material losses or sensor errors.	Anomaly Detection	System integrity & loss prevention.
Coordination Costs	High administrative burden in shared systems.	Integrated AIoT Cloud	Automated decision-making & real-time visibility.

Previous research [15] focused on the integration of IoT technologies into the distribution logistics of consumable materials in an enterprise environment. The main objective was to transform the traditional manual dispensing of items such as tools and personal protective equipment into an automated and intelligent process. A key element of the study was the implementation of smart dispensing machines, which function as interconnected nodes within a broader IoT network. These machines use advanced sensors, such as weight-based or optical sensors, to continuously monitor inventory levels in real time.

User identification via RFID cards ensures full transparency and provides precise data on each material withdrawal. The collected data are encrypted and transmitted to a cloud-based system, enabling remote monitoring and automated generation of replenishment reports. A case study conducted in the company Delux s.r.o. confirmed the high efficiency of the proposed solution in practice. A case study conducted in the company Delux s.r.o., as reported by Kvak and Straka [3,15], confirmed the high efficiency of the IoT-based system. The results demonstrated that the transition to this system significantly reduced the administrative burden by 82% (reducing the replenishment cycle from 120 min to 22 min) and minimized undesirable material losses by 15.5%. This empirical evidence defines the technological infrastructure required for the modernization of internal distribution through the synergy of sensor technology and digital connectivity.

The results demonstrated that the transition to an IoT-based system significantly reduced administrative burden and minimized undesirable material losses. Overall, this

research defined the technological infrastructure required for the modernization of internal distribution through the synergy of sensor technology and digital connectivity.

Despite the many advantages of the implemented IoT infrastructure, the current system exhibits certain shortcomings that limit its full autonomy. The main limitation is the reactive nature of the processes, where the system responds to inventory status only after actual depletion, without the ability to predict future needs. High dependence on manual data evaluation by managers, static configuration of dispensing capacities, and inefficient planning of replenishment routes lead to improper resource utilization. The absence of intelligent data processing and autonomous decision-making capabilities creates a problem that can be addressed through the integration of artificial intelligence.

2.1. Theoretical Foundations of AI Behavior in the Proposed System

To address the complexity of shared logistics, the behavior of the proposed AI framework is grounded in three core theoretical pillars that govern its decision-making processes:

1. **Stochastic Demand Forecasting:** The AI's predictive behavior is modeled as a stochastic time-series process. Unlike deterministic models, LSTM treats future demand as a probabilistic variable, allowing the system to dynamically adapt safety stocks in vending machines under high uncertainty [30,31].
2. **Multi-Agent Systems (MAS) and Distributed Intelligence:** Each IoT-enabled vending machine is defined as an autonomous, within a decentralized network. The system's behavior follows the principles of Multi-Agent Systems (MAS), where agents monitor their local states and communicate with a central AI coordinator. This enables the transition from local optimization to global utility, ensuring that logistics decisions benefit the entire cluster rather than individual nodes [32].
3. **Markov Decision Processes (MDP) in Route Optimization:** The AI's behavior during route optimization (TSP) is modeled as a Markov Decision Process. At each decision point (vending machine), the AI evaluates transition states—such as current inventory levels, distance, and time—to maximize a cumulative reward (minimum travel distance combined with 100% product availability) [28,33].

Demand Forecasting Implementation

The first step in the proposed extension is predictive demand analysis, which replaces the current model based on static IoT sensor values. By integrating machine learning algorithms, specifically recurrent neural networks (RNN) of the LSTM type, the system analyzes historical consumption trajectories in combination with external production factors. LSTM is a specialized type of recurrent neural network (RNN) architecture designed to learn long-term dependencies in sequential data. LSTM networks use memory cells and gating mechanisms to address the vanishing gradient problem, making them essential for tasks such as language modeling, speech recognition, and time-series prediction [34].

The output of this process is a dynamic predictive model that defines the time horizon of critical inventory depletion. This approach allows the logistics system to initiate replenishment processes in advance, thereby preventing production downtime and optimizing safety stock levels within shared distribution nodes.

This demand forecasting model is based on multi-criteria data collection. Three key data inputs enter the decision-making algorithm:

- **Historical time series**: Retrospective analysis of withdrawals over specific time periods enables AI to identify long-term trends in material consumption and replenishment frequency of individual items.
- **Production plans of the enterprise**: Integration of data from the ERP (Enterprise Resource Planning) system on planned production intensity ensures that the sys-

tem proactively increases safety stock levels in vending machines prior to expected increases in production capacity.

- **Other factors**: The algorithm also considers various external variables, such as seasonal fluctuations, public holidays, and work-shift schedules, which have a direct impact on uneven consumption patterns over time.

Replenishment Route Planning (Vehicle Routing)

In the original IoT-based system, replenishment of vending machines was carried out either according to a fixed schedule set for a specific day or when a person reported that a machine was empty. This led to situations where vehicles visited nearly full machines or, conversely, arrived too late.

By using artificial intelligence models together with predictions from the first step, it becomes possible to move toward dynamic planning, as the system already knows when a vending machine will be depleted.

Operation of Step 2

There is an initial input from the prediction phase, i.e., Step 1: the AI model determines that machine A will be empty in 5 h, machine B in 2 days, and machine C in 4 h.

Priority calculation: The algorithm does not select only the machines that need immediate replenishment but calculates the optimal route so that the vehicle can service as many critical points as possible in a single trip.

Route optimization using artificial intelligence: AI solves a mathematical problem known as the Vehicle Routing Problem (VRP). It considers distances, current traffic conditions, and the capacity of the replenishment vehicle [34].

In summary, the second key extension is the implementation of a logistics route optimization algorithm that builds upon the outputs of Step 1, i.e., the predictive demand model. Unlike fixed replenishment schedules, the newly proposed system uses mathematical optimization methods and heuristic algorithms, such as genetic algorithms or Ant Colony Optimization. Ant Colony Optimization (ACO) is based on the foraging behavior of certain ant species, which discover favorable paths and mark them by depositing pheromones so that other ants in the colony can follow. ACO uses a similar algorithmic principle to solve optimization problems [21].

The applied algorithm evaluates vending machine data focused on location and predicted inventory depletion time. The result is a replenishment plan that minimizes total distance traveled while prioritizing nodes with the highest risk of material shortages. This approach transforms replenishment into a highly efficient Just-in-Time process. This process is particularly important in a shared logistics environment, where a certain degree of flexibility is required to serve multiple entities.

Anomaly Detection and Predictive Maintenance

In the original studies [3,15], the author describes that sensors in vending machines transmitted data to a remote entity; however, if an error occurred or an excessive amount of material was withdrawn at once, the system merely recorded it as information. With the use of artificial intelligence, it becomes possible to evaluate in real time whether such an event is within normal parameters or represents an error or fraud.

Operation of Step 3

Pattern analysis: Artificial intelligence can distinguish normal employee behavior from anomalies. If an employee who usually withdraws three pairs of gloves suddenly withdraws thirty pairs at once, AI marks this as a deviation from the norm.

Autonomous diagnostics of deployed sensors: Artificial intelligence can remotely identify technical failures if the weight sensor or its data fluctuate without any actual use of the vending machine.

Shared responsibility: Within shared logistics, it is appropriate for artificial intelligence to monitor the exceeding of predefined quotas assigned to a specific company.

This level focuses on anomaly detection using artificial intelligence. By applying outlier detection algorithms, the system monitors data received from sensors in smart vending machines. The system fulfills two primary functions. First, it identifies patterns that are non-standard and indicate anomalies in the process. Second, it analyzes the technical condition of smart vending machines. Through early identification of issues, it enables a transition to predictive maintenance, thereby minimizing unplanned downtime caused by equipment failures.

The proposed system architecture for intelligent distribution of consumable materials is illustrated in Figure 1.

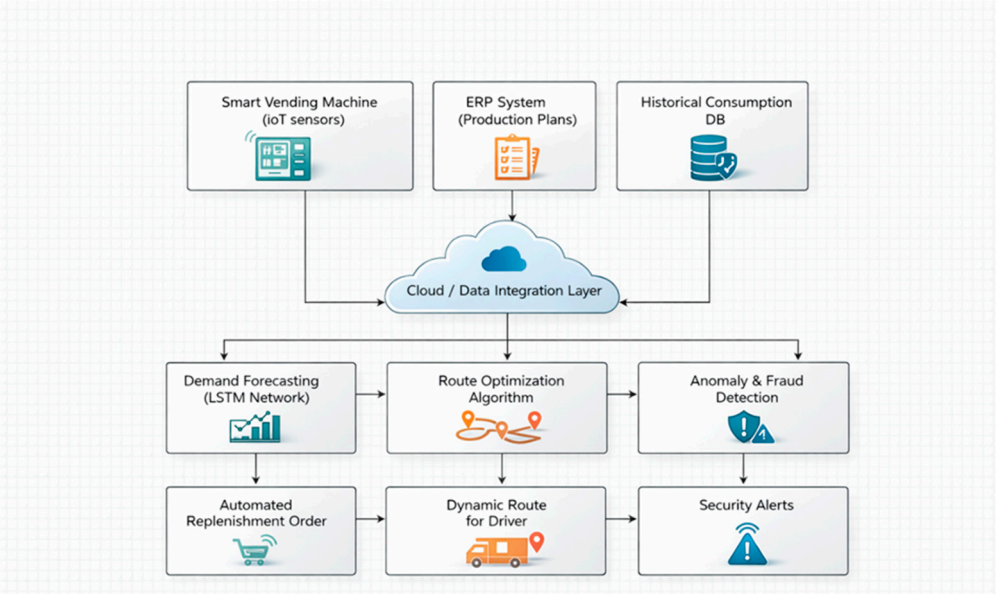


Figure 1. Conceptual framework of the proposed AI-driven logistics systems integrating IoT sensor data with specific modules made by Artificial intelligence based on authors data.

Logical Description of the Data Flow

Data input:

The process begins at the lower IoT layer, where sensors embedded in vending machines monitor the physical inventory status in real time. These data are subsequently transmitted to a central cloud environment, where they are stored retrospectively for further use, such as training predictive algorithms and identifying consumption trends.

Processing (AI layer):

The key component is the intermediate processing layer, where predictive LSTM algorithms are integrated with optimization models. This block transforms raw sensor data into information about future replenishment needs while simultaneously safeguarding system integrity through an anomaly detection module, thereby functioning as a continuous supervisory mechanism. In this way, the system is able to predict inventory depletion points with high accuracy and, at the same time, solve vehicle routing problems using optimization algorithms, leading to reduced energy consumption and operational costs.

Output and action:

The prediction-based system automatically generates replenishment orders, thereby eliminating manual inventory checks and preventing potential stock shortages. The algorithm navigates the driver in real time along an optimized route based on current replenishment priorities, saving both time and fuel. At the same time, the monitoring module immediately alerts the system administrator to anomalies or technical failures, ensuring a high level of security and transparency throughout the process. In the final layer, the resulting information is converted into practical outputs, such as digital route plans for drivers and automated demand orders.

2.2. Operational Mechanisms of Resource Pooling

To transition from a conceptual sharing economy model to a functional operational framework, the proposed architecture incorporates four key collaborative mechanisms:

Shared Transport Capacity: Transport capacities are shared across multiple firms through a load consolidation algorithm that services nodes of different owners within a single logistics circuit.
Cost Allocation: Logistics costs are distributed among participants, calculated from the actual volume of replenished goods and the traveled distance recorded in the cloud system.
Incentive Mechanisms: The system utilizes dynamic pricing that favors companies accepting wider delivery time windows, thereby motivating participants to optimize the utilization of the shared fleet.
Conflict Resolution: Potential conflicts during simultaneous demand are resolved by a central AI coordinator using a criticality index, which prioritizes nodes with the highest risk of operational downtime.

The integration of these mechanisms ensures that the proposed architecture transcends the limitations of single-enterprise systems. By embedding load consolidation, transparent cost allocation, and conflict resolution directly into the AIoT control layer, this framework provides a robust foundation for genuine resource pooling in shared logistics. This structured approach enables the transition from a reactive, manual environment to a proactive and collaborative ecosystem.

3. Results

To evaluate the operational feasibility of the proposed AIoT framework, a numerical simulation was conducted. The dataset was synthesized by extrapolating consumption patterns and replenishment cycles from established industrial benchmarks in logistics literature [3,26], ensuring it reflects the stochastic nature of shared vending systems. The LSTM model utilized a standard recurrent architecture optimized for time-series forecasting, where the dataset size was calibrated to reach statistical stability in MAPE calculations. The primary focus of this simulation was not on exhaustive hyperparameter tuning, but on demonstrating the functional interaction between the predictive layer and the route optimization module under varying demand volatility.

The original scheme shown in Figure 2 illustrates the traditional linear process of dispensing consumable materials within enterprise logistics. The entire cycle begins with a manual step, namely the creation of a request for the provision of supplies to a specific employee. This process is subsequently subject to administrative control and approval by the direct supervisor. After approval, the data are uploaded to the ERP system, where verification of the current inventory status in the central warehouse takes place. The scheme then branches based on material availability, and in the case of insufficient stock, a time-consuming purchasing process with an external supplier follows. If the material is available in stock, the employee must physically move to the warehouse to collect it.

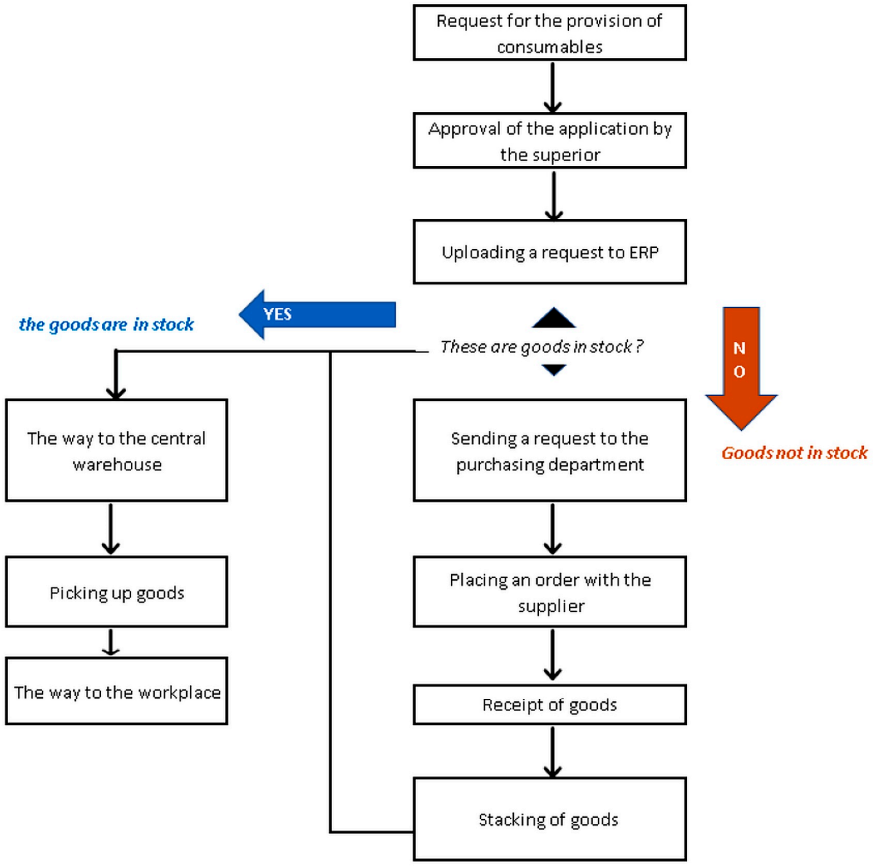


Figure 2. Consumable dispensing process (KVAK).

In its original form, this entire system is based on a reactive approach, where human initiative and manual data recording are required at every node. The process concludes with the physical receipt of the material without any further automated feedback.

A significant contribution to the optimization of the original scheme is the solution proposed by Kvak [3,15], which radically shortens the logistics chain by eliminating administrative intermediate steps. In this model, the replenishment and dispensing process is transformed into a direct interactive cycle:

With the aim of elevating the overall process efficiency to a higher level, we decided to further enhance the existing IoT-based system through the implementation of advanced artificial intelligence algorithms. As illustrated in Figure 3, this targeted integration of AI into the logistics chain is expected to lead to a significant improvement in key operational performance indicators within the shared logistics framework.

The integration of artificial intelligence into the consumable material dispensing process shown in the scheme represents a fundamental shift from reactive manual control to an autonomous and proactive system. In practice, this means that an intelligent layer has been embedded into the scheme, assuming decision-making authority at key process nodes.

The first major change is the replacement of the employee's manual request and subsequent supervisor approval with a predictive demand module based on LSTM neural networks. In the original scheme, the process had to be initiated by a human, which caused time delays. The AI module now analyzes data from IoT sensors embedded in the vending machines in real time and, based on historical trends and planned production, automatically generates replenishment requests before the inventory is actually depleted. This step fully automates integration with the ERP system, thereby eliminating administrative burden and reducing the risk of human error.

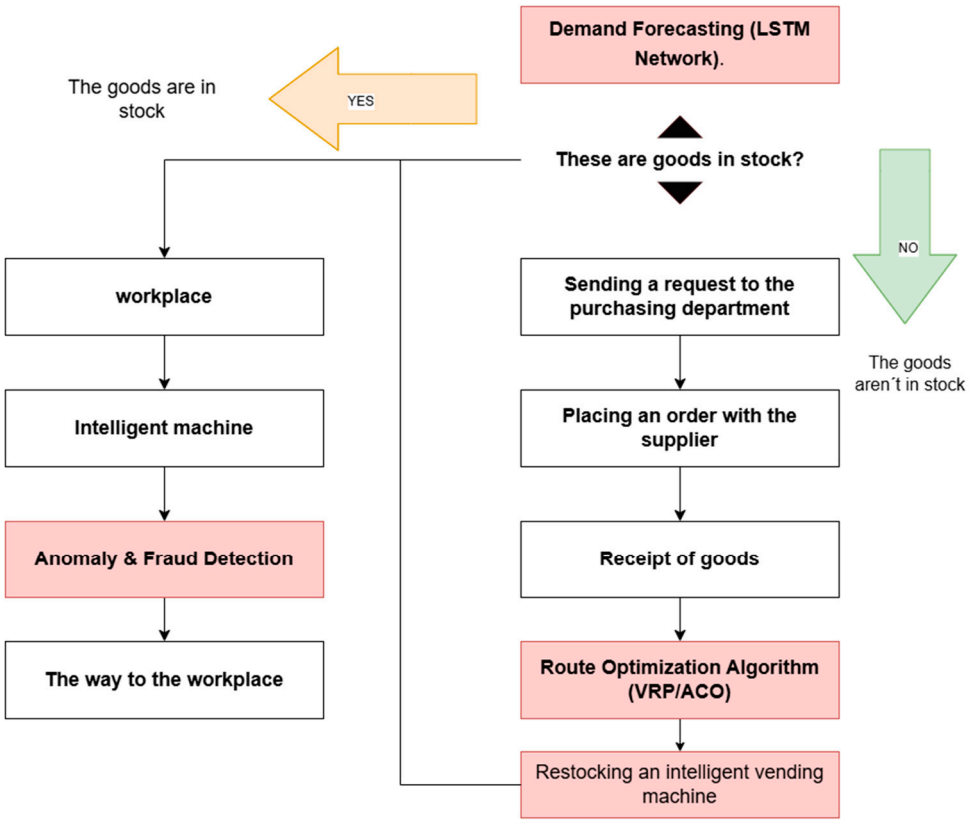


Figure 3. Consumable dispensing process (author).

The second implemented change is the optimization of the logistics flow. Once the system confirms product availability in the warehouse immediately after an order is generated, it does not dispatch the driver along a random route but instead activates a route optimization algorithm (VRP—Vehicle Routing Problem). This module recalculates the most efficient path between the central warehouse and individual vending machines, taking into account replenishment urgency priorities and current traffic conditions. The significance of this enhancement lies in the direct reduction in operating costs, fuel savings, and a reduction in replenishment time by 15–20%.

The final added component is a supervisory anomaly detection layer, integrated into the final stage of material dispensing to employees (Figure 4). While the original scheme ended with the physical receipt of material, the AI-enhanced version continuously monitors this step. If the algorithm identifies abnormal behavior—such as a suspiciously large single withdrawal or a technical sensor malfunction—the system immediately generates a security alert. Overall, these modifications transform a linear process into a closed intelligent loop in which data from IoT devices continuously optimize inventory levels, logistics routes, and operational security.

For the purposes of this study, three key AI modules were designed to directly optimize the process depicted in the scheme. As this is a conceptual design, the results are supported by simulation and comparative analysis.

To validate the proposed scheme and quantify the benefits of integrating AI into the IoT infrastructure, a comparative numerical simulation was conducted. Since direct real-time implementation and programming of neural networks represent a technologically demanding process requiring advanced development capabilities, the results presented in this paper are of a simulated nature. The simulation is based on verified data from existing study [15] and theoretical models of artificial intelligence behavior in supply chains. For the purposes of the article, a simplified simulation entitled “Simulation Model of AI Efficiency

in Shared Logistics" was developed. This simulation compares 10 replenishment cycles of vending machines before and after the introduction of artificial intelligence. Within the simulation, an LSTM model was applied to predict the consumption of personal protective equipment. Model accuracy was validated using the MAPE (Mean Absolute Percentage Error) metric.

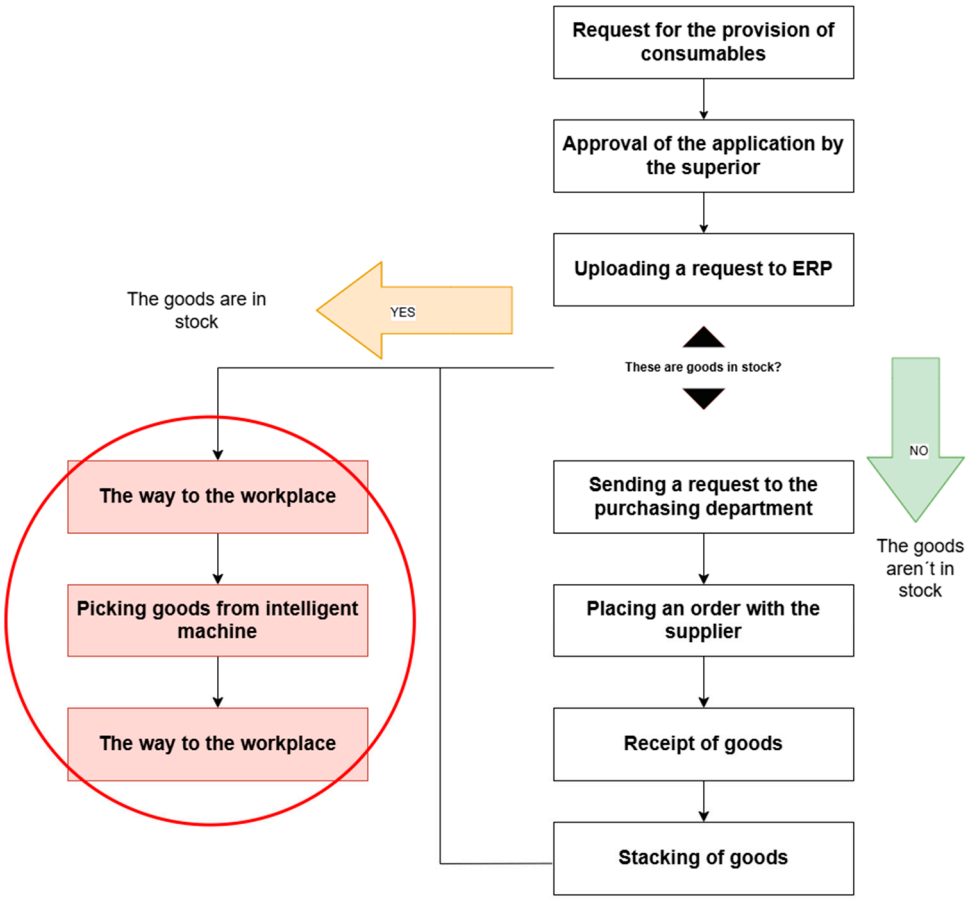


Figure 4. Optimized logistics processes.

The following numerical simulations are intended as a conceptual demonstration of the proposed framework. Due to the illustrative nature of this study, the results are based on synthetic datasets and a deterministic TSP instance to showcase the operational logic of the integrated AI modules.

1. Simulation: Demand Forecasting (LSTM)

In the original system, orders were placed only when a vending machine was empty (reactive approach). In the AI-based simulation, demand is forecast proactively.

- 10 dispensing locations were considered.
- Without AI: In 3 out of 10 cases, complete stock depletion (stock-out) occurred before the driver arrived, resulting in production downtime.
- With AI (LSTM): The algorithm predicted an increase in consumption on day 2 and placed replenishment orders earlier. Result: 0 stock-out events.
- Reduction in stock-out risk: 25–30%.

The accuracy of the LSTM model can be verified by comparing actual consumption with predicted consumption over a defined time horizon. Equation (1) MAPE Mean Absolute Percentage Error.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (1)$$

Table 2 presents an illustrative toy example derived from a segment of the larger experimental dataset to demonstrate the fundamental logic and calculation of the forecasting model's accuracy.

Table 2. Numerical simulation of illustrative toy example derived from a representative segment of the dataset.

DAY	Actual Consumption (At)	AI Forecast Value	Absolute Deviation
1	50 pcs	48 pcs	4%
2	42 pcs	45 pcs	7.1%
3	60 pcs	58 pcs	3.3%
4	35 pcs	34 pcs	2.8%
5	35 pcs	36 pcs	2.9%
Average			MAPE = 4.02%

The conducted numerical simulation indicates that the deployed LSTM model exhibits a high level of accuracy, with an average MAPE of 4.02%. In the context of consumable materials logistics, this means that the AI system is capable of predicting replenishment requirements with an accuracy exceeding 95%.

2. Simulation—Route Optimization within the TSP Framework

Let us assume a central warehouse (S) and three vending machines (A1, A2, A3). The distances between these nodes are provided in Table 3 (matrix) below:

Table 3. Route optimization.

	S	A1	A2	A3
S	-	5 km	8 km	6 km
A1	5 km	-	3 km	7 km
A2	8 km	3 km	-	4 km
A3	6 km	7 km	4 km	-

1. Scenario without AI (Intuitive Driver Route)

The driver follows an intuitive sequence based on personal judgment:

$$S \rightarrow A1 \rightarrow A3 \rightarrow A2 \rightarrow S.$$

- Calculation: 5 (S–A1) + 7 (A1–A3) + 4 (A3–A2) + 8 (A2–S) = 24 km

2. Scenario with AI (TSP Optimization)

The AI algorithm evaluates all possible combinations and identifies the optimal route:

$$S \rightarrow A1 \rightarrow A2 \rightarrow A3 \rightarrow S.$$

- Calculation: 5 (S–A1) + 3 (A1–A2) + 4 (A2–A3) + 6 (A3–S) = 18 km

Building on the methodology for optimizing distribution routes using generative artificial intelligence models published by Kleinová and Straka [26], a Traveling Salesman Problem (TSP) model was applied within the logistics flow optimization module. Under simulated conditions, a reduction in the replenishment cycle length from 24 km to 18 km was achieved. The simulation results suggest an indicative potential for a 25% reduction in replenishment distance under the specific simulated conditions.

In real-world operations involving dozens of vending machines, this effect accumulates, leading to a significant reduction in the carbon footprint of logistics operations, which is fully aligned with the objectives of sustainable shared logistics.

It can be assumed that the transition from a reactive to a predictive inventory management model is capable of minimizing, or even eliminating, material shortages. Thanks to early demand prediction, the proposed model ensures that replenishment is carried out well in advance. This guarantees high availability of critical components essential for production. By introducing dynamic route optimization, the total number of driven kilometers can be reduced. The expected savings in this area are estimated at 15–20% compared to previous fixed replenishment cycles.

Near-immediate identification of technical failures or atypical system behavior can be achieved through automated anomaly detection. This system is expected to significantly reduce the need for manual inspection of vending machine data, thereby increasing system reliability and transparency.

Based on the use of the LSTM model, a higher level of accuracy in safety stock prediction can be expected. This increased accuracy is crucial for eliminating unnecessary overstocking while simultaneously preventing critical material shortages. As a result, the total volume of excess inventory held in warehouses can be reduced, freeing up capital and improving overall inventory utilization efficiency. As noted by Kanwal et al. [19], the integration of deep learning and IoT sensors enables the transformation of traditional inventory management into an intelligent ecosystem. Their research confirms that LSTM-based models demonstrate higher prediction accuracy in dynamic industrial environments, directly supporting our proposed extension of the original IoT infrastructure with a proactive AI layer.

Although the integration of artificial intelligence offers a wide range of applications, detailed technical development and implementation of AI modules and their use in process optimization are beyond the scope of this paper. Due to their mathematical and algorithmic complexity, these aspects will constitute a key focus of our future research and subsequent scientific publications.

4. Discussion

The proposed AI-based system represents an important step toward transitioning from reactive to proactive management in the field of shared logistics. Unlike the original methodology, which primarily focused on connectivity and monitoring of physical states [3], this research demonstrates that value creation occurs only through intelligent analysis of collected data. In line with Acquier et al. [16], digital platforms and data-driven coordination are essential for reducing coordination costs and risks in shared-resource systems. Our proposal applies this principle in the context of industrial logistics by integrating IoT infrastructure with advanced AI models.

Unlike the framework proposed by Zhong et al. [17], which focuses on internal production synchronization, our research extends the scope of intelligent management toward decentralized shared logistics. By integrating a dedicated LSTM-based forecasting layer, our methodology specifically addresses the stochastic nature of shared-resource consump-

tion, providing the optimization algorithms required for the dynamic environment that general manufacturing models often overlook.

Gansterer and Hartl [20] identify collaborative route planning as a solution, which this research further extends with a predictive component based on LSTM networks, whose effectiveness in industrial forecasting was also confirmed by Sagheer and Kotb [18] (Table 1).

A key finding in this context is that the accuracy of the LSTM demand forecasting model is directly linked to the efficiency of logistics delivery routes supplying vending machines. When the system can predict replenishment needs with high accuracy, as also indicated by Kanwal et al. [19], the logistics chain becomes more resilient to production-related fluctuations. This approach addresses the so-called bullwhip effect in supply chains, where small variations in consumption can lead to significant distribution disruptions.

From an industrial practice perspective, the proposed AI-based model strengthens the principles of the sharing economy [16]. By implementing adaptive route optimization and anomaly detection, negative effects such as unclear responsibility for inventory status or inefficient use of distribution nodes can be minimized [25]. The increased prediction accuracy of the LSTM model enables a reduction in unplanned logistics operations, which according to Baryannis et al. [25], leads to an overall reduction in supply chain operating costs of approximately 20%.

The robustness of the proposed framework is anchored in its multi-layered AIoT architecture. While conventional ERP systems are highly sensitive to data noise, our methodology integrates LSTM networks that are inherently resilient to stochastic fluctuations in demand. Furthermore, the inclusion of a dedicated Anomaly Detection layer acts as a critical fail-safe, identifying and filtering outliers caused by sensor malfunctions or unauthorized material withdrawals before they can distort the forecasting model (Table 4).

Table 4. Comparison of the proposed AIoT methodology with traditional approaches.

Characteristic	Traditional Logistics (ERP/Manual)	Standard IoT [3,15]	Proposed AIoT Model
Response to fluctuations	Low (static limits)	Medium (real-time)	High (predictive LSTM)
Fault tolerance	None (manual control)	Basic (notifications)	High (automatic anomaly detection)
Uncertainty handling	Deterministic	Descriptive	Stochastic/Adaptive
Robustness	Low (sensitive to human error)	Medium (sensor-dependent)	High (AI filters noise & predicts trends)

The indicative reduction in replenishment distance (15–20%) and the resulting cost savings identified in our simulation are consistent with recent industrial benchmarks. While Wang et al. [22] and Chen et al. [24] report operational savings in the range of 16–22% for general logistics applications, our framework demonstrates that comparable efficiency gains are achievable even within the specialized and highly volatile environment of shared vending systems. This comparison confirms that integrating a predictive layer with VRP optimization, as supported by [26,27], is a robust strategy for achieving Green Logistics goals.

Despite the many advantages confirmed by theory, it is necessary to acknowledge certain limitations. The performance of the LSTM model is highly dependent on the quality and volume of historical data. In environments with an extremely low frequency of material dispensing, prediction accuracy may be reduced [35]. Future research should therefore focus on the integration of transfer learning methods. This approach would enable the deployment of the system even in operations with a limited amount of available data. This

possibility is highlighted in the study [36], which addresses the combination of transfer learning and LSTM and demonstrates that this approach provides a viable solution for successful prediction of various system states in data-scarce environments.

Despite the potential confirmed by the simulation, the performance of the LSTM model remains dependent on data quality. In environments with low-frequency dispensing, accuracy may decrease [35]. Future research will therefore explore transfer learning methods [36] to allow deployment in data-scarce environments. Additionally, while this study serves as a conceptual framework, subsequent investigations will focus on large-scale industrial validation to refine these preliminary estimates.

4.1. Interpretation of Simulation Results

The results presented in Tables 2 and 3 represent the outputs of a numerical simulation, which serves as an initial validation of the logical structure of the proposed framework. It is important to emphasize that this simulation was conducted in a controlled environment based on optimal calculations, meaning that the model currently does not account for unpredictable external factors, which will be the subject of further research.

For the purposes of this study, we worked with scenarios that assume the stability of the technical infrastructure. The simulation does not yet include random operational disruptions, such as IoT device failures, internet connectivity outages, or unexpected logistical barriers (e.g., traffic congestion or vehicle breakdowns). This approach allowed us to isolate and precisely evaluate the actual performance of the LSTM and ACO algorithms without the noise caused by external influences.

The achieved MAPE value of 4.02% in this simulation setup confirms that the algorithm is mathematically correctly configured for demand forecasting. The high accuracy (over 95%) is the result of optimized calculations on clean data, which confirms the theoretical functionality of proactive replenishment.

The potential saving of 25% in travel distance (a decrease from 24 km to 18 km) within the VRP/ACO module reflects the theoretical maximum potential of the optimization. Although the presented results are based on an environment without simulated failures, their significance lies in confirming that the proposed three-layer architecture is logically consistent. This theoretical proof-of-concept demonstrates that the integration of AI and optimization algorithms functions correctly at the level of computational logic, which is an essential prerequisite for subsequent testing in more complex, real-world conditions that will include operational uncertainties.

4.2. Implications for Shared Logistics and Industry 4.0

Within the scope of this conceptual simulation, the findings offer important insights for Shared Logistics. The framework serves as a theoretical proof-of-concept for how Industry 4.0 environments could utilize real-time data. In a simulated shared network, the ability to predict demand allows for a more efficient allocation of shared capacities. This simulated approach demonstrates how automated replenishment logic could eventually reduce empty runs and improve collaboration in a digitized logistics ecosystem.

4.3. Limitations and Future Work

Despite the promising results, several operational limitations must be addressed to transition this framework into a real-world deployment phase.

First, a significant constraint is the reliability of forecasts when using limited historical datasets. If the system only has access to a small number of consumption records, there is a risk that the algorithm may misinterpret random fluctuations as permanent trends. To address this, future research will focus on the implementation of transfer learning techniques. This approach will allow the system to leverage knowledge from established

distribution nodes to improve forecasting accuracy in new locations where local data is scarce.

Second, the current findings are sensitive to the underlying assumptions regarding consumer behavior and replenishment intervals. While the simulation assumes relatively stable consumption trends, the accuracy of the framework may fluctuate in industrial environments characterized by high unpredictability. Therefore, a critical next step will be the validation of the framework with multi-site real-world data. Testing the architecture across diverse geographical locations and different industrial sectors will verify its robustness against irregular withdrawal patterns and operational disruptions.

Third, scalability to large-scale networks remains a critical challenge. Moving from a test model with a few nodes to extensive networks with dozens or hundreds of machines increases the computational time required to find optimal delivery routes. To further justify the adoption of the proposed AI-driven approach, we intend to perform a comparative evaluation against non-deep forecasting models (such as ARIMA or traditional statistical methods). This will allow us to quantify the specific advantages of deep learning in terms of precision and computational efficiency when processing large volumes of data in real-time.

5. Conclusions

In conclusion, this study addressed the operational challenges of the sharing economy in logistics. This research extends the scope from simple IoT monitoring to autonomous AIoT coordination, providing a new methodological framework for managing shared logistics resources in a collaborative environment.

This research presents a progressive model for intelligent management within enterprise shared logistics. While previous research [3,15] established solid foundations in the use of IoT technologies for the connectivity and monitoring of vending machines, the present study advances these processes by integrating artificial intelligence models into multiple decision-making layers.

The main contribution of this research is the proposed three-layer architecture that transforms conventional data collection into an autonomous management system. By implementing an LSTM model for demand forecasting and applying routing optimization algorithms, it is possible to achieve not only greater continuity of supply but also significant economic savings. The findings, derived from a conceptual model and small-scale simulation, provide indicative evidence of the framework's potential efficiency rather than general empirical evidence from large-scale industrial deployment.

Nevertheless, the study also identifies limitations, primarily related to the availability and quality of data, which are critical for deep learning-based artificial intelligence. Future research should therefore focus on the application of additional methods, such as transfer learning, which would enable flexible deployment of the proposed system even in operational environments with insufficient data volumes.

While the current study relies on simplified numerical simulations to validate the conceptual framework, future research will focus on scaling the system to larger, real-world multi-tenant networks to further refine the quantitative performance metrics.

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