Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 7 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i07.61239

PAPER

A Mobile Agent–Based Method for Logistics Coordination Management

Yong Chen(✉)

Shangqiu Polytechnic, Shangqiu, China

13507699675@163.com

ABSTRACT

To address the fundamental limitations of conventional logistics coordination systems—including delayed responses in dynamic environments, low collaboration efficiency, and rigid resource allocation—a cloud–edge–end collaborative mobile agent management framework for logistics scenarios was proposed by integrating recent advances in mobile agents, mobile edge computing, and digital twin technologies. This study introduced three major technical innovations. At the architectural level, a digital twin–driven, hierarchically decoupled open ecosystem was constructed, overcoming the constraints of traditional centralized control paradigms. At the mechanism level, a multimodal coordination mechanism was designed, achieving dynamic multi-issue task allocation, supporting context-aware adaptive decision-making, and enhancing the handling of complex problems. At the technical level, mobile edge computing-enabled task offloading strategies and lightweight real-time digital twin simulation were integrated to improve real-time responsiveness and reduce device energy consumption in mobile environments. To validate the effectiveness of the proposed framework, two representative experimental scenarios were constructed: a warehouse–distribution integrated automated guided vehicle coordination scenario and an urban last-mile hybrid delivery scenario involving unmanned aerial vehicles and automated guided vehicles. Comparative simulation experiments were conducted using an AnyLogic–ROS co-simulation platform. The results demonstrate that the proposed method significantly outperformed conventional centralized scheduling and standard multi-agent approaches in terms of end-to-end decision latency, task conflict resolution success rate, energy consumption, and adaptability to dynamic environments. These findings provide an innovative paradigm and robust technical support for the large-scale application of mobile agent technologies in logistics coordination management.

KEYWORDS

mobile agents, logistics coordination management, cloud–edge–end collaboration, digital twin, mobile edge computing, multi-agent coordination algorithms

Chen, Y. (2026). A Mobile Agent–Based Method for Logistics Coordination Management. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(7), pp. 168–182. https://doi.org/10.3991/ijim.v20i07.61239

Article submitted 2026-01-15. Revision uploaded 2026-02-24. Final acceptance 2026-02-26.

1 INTRODUCTION

In the ongoing digital transformation of the logistics industry, increasing order fragmentation, environmental dynamism, and resource heterogeneity have become prominent characteristics [1, 2], imposing stringent requirements on real-time responsiveness and global optimization in logistics coordination management. Most existing logistics systems continue to rely on centralized scheduling or rigid distributed architectures. When confronted with dynamic operating conditions such as order fluctuations, traffic disruptions, and equipment failures, these systems commonly suffer from response delays, inefficient resource allocation, and frequent task conflicts due to insufficient mobility adaptation, delayed edge-level coordination, and fragmented human–machine–object interactions [3]. In centralized architectures, redundant command transmission hierarchies are poorly matched to the real-time decision-making demands of mobile carriers, whereas conventional distributed schemes lack effective coordination mechanisms and are prone to global resource waste, ultimately constraining overall system performance [4]. The integrated application of mobile agent technology, mobile edge computing, and digital twin technology has been recognized as a critical enabler for reconfiguring logistics coordination paradigms. Autonomous perception and migration capabilities of mobile agents enable distributed coordination, mobile edge computing facilitates latency reduction through computational offloading to the network edge, and digital twins establish virtual–physical mappings to support dynamic simulation and decision-making [5]. However, a unified coordination framework tailored to logistics scenarios has yet to be established in existing studies. Persistent challenges remain in balancing decentralization with centralized optimization, designing real-time negotiation mechanisms for mobile devices, and deeply integrating lightweight technologies with mobile carriers—limitations that are particularly evident from the perspective of mobile technology–oriented research venues [6]. Accordingly, this study focuses on the deep integration of mobile agents and logistics coordination through architectural innovation, mechanism design, and technological integration, with the objective of providing technical support for the flexible upgrading of logistics systems.

The inherent limitations of traditional architectures continue to hinder the achievement of core logistics coordination objectives. Centralized scheduling approaches, which depend on cloud-based unified decision-making, exhibit delayed responses to dynamic changes in mobile carrier locations and unexpected operating conditions [7, 8]. In contrast, distributed approaches lack cross-regional coordination capabilities, and autonomous decision-making by individual mobile units often results in global conflicts [9]. Fundamentally, these issues arise from inadequate adaptation of conventional architectures to the mobility characteristics of logistics systems, insufficient coordination between edge and terminal layers, and persistent barriers in human–machine–object interactions, making it difficult to simultaneously ensure real-time responsiveness and optimization efficiency [10, 11]. Mobile agent technology provides a key pathway for restructuring logistics coordination models; however, existing applications remain confined to isolated functional stages and relatively simple scenarios [12, 13]. Systematic designs that integrate multiple enabling technologies are still lacking, and key challenges—such as real-time coordination scheduling in mobile environments, cross-domain resource orchestration, and low-power computing—have not been effectively addressed [14, 15]. In response, the core research objectives and problems are distilled in this study to develop a digital twin–driven cloud–edge–end collaborative mobile agent logistics management framework, aiming to overcome technical bottlenecks in real-time dynamic coordination, cross-domain resource scheduling, and lightweight mobile interaction. By addressing the fundamental limitations of conventional systems in dynamic environments, enhanced adaptability to complex operating conditions is achieved, thereby providing a technical paradigm and practical foundation for the large-scale deployment of mobile agent technologies in logistics systems.

The remainder of this study is structured as follows: Section 2 systematically elaborates the core components, functional allocation, and coordination logic of the cloud–edge–end collaborative architecture. Section 3 provides an in-depth discussion of the core algorithms, mobile edge computing-enabled task offloading strategies, and lightweight digital twin techniques. Section 4 quantitatively evaluates the superiority and feasibility of the proposed approach through experiments and tests. Section 5 synthesizes the main findings, analyzes challenges associated with real-world deployment, and outlines directions for future research.

2 A MOBILE AGENT–BASED LOGISTICS COORDINATION MANAGEMENT FRAMEWORK

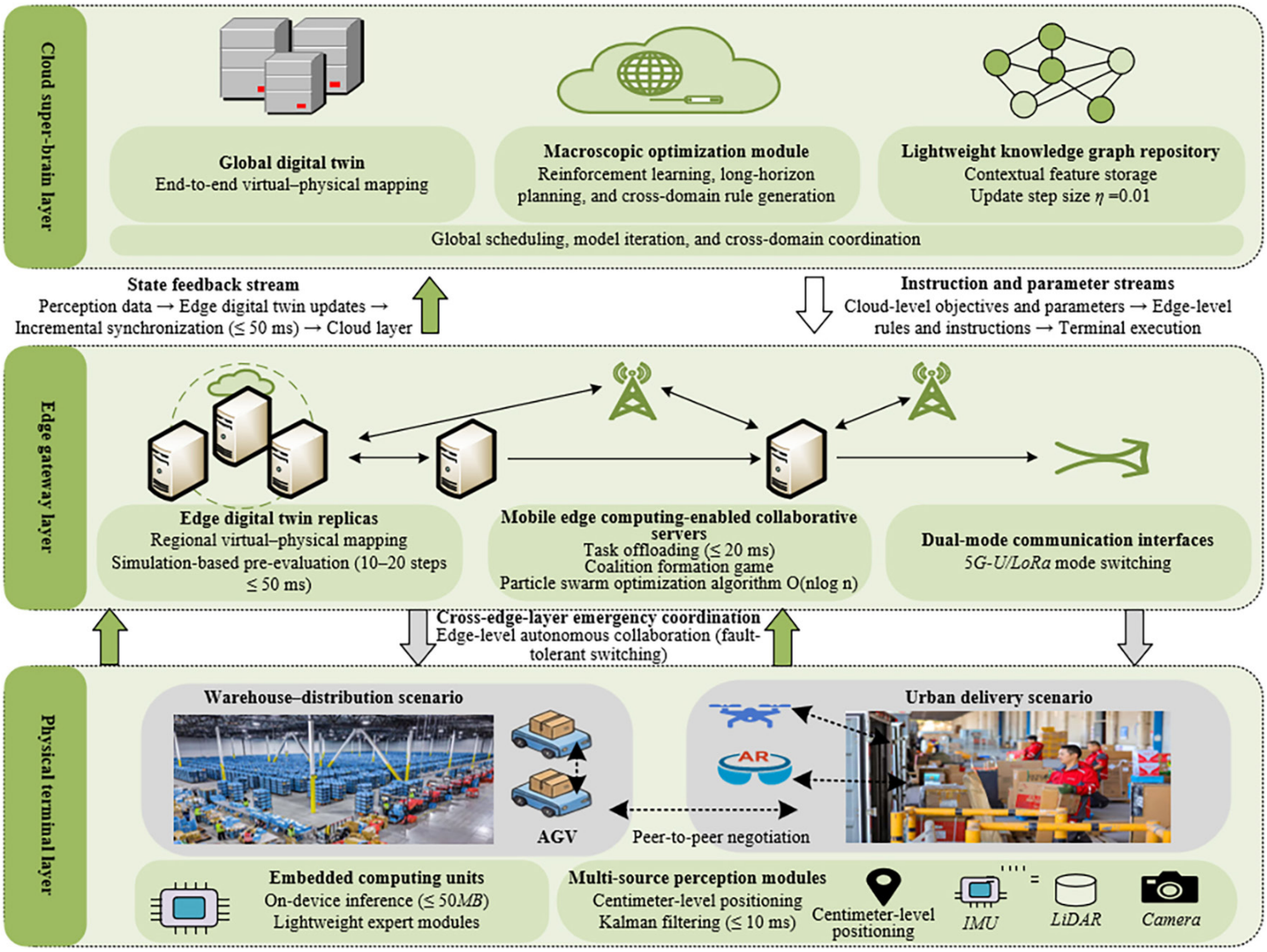

Fig. 1. Architecture of a digital twin–driven cloud–edge–end collaborative mobile agent logistics management system

As illustrated in Figure 1, a digital twin–driven cloud–edge–end collaborative logistics management architecture is established. The architecture is vertically decoupled into three layers: a cloud super-brain layer responsible for global macroscopic optimization, an edge gateway layer supporting region-level agile coordination, and a physical terminal layer executing concrete operational tasks. Strategy coupling between the cloud and edge layers is enabled through multi-level digital twin models, jointly guiding heterogeneous terminals—such as automated guided vehicles and unmanned aerial vehicles—to operate efficiently in both warehouse and urban logistics scenarios. Through hierarchical decoupling, the proposed architecture overcomes the limitations of traditional centralized control and achieves a dynamic balance between decentralized autonomous coordination and cloud-level centralized optimization. This balance is realized through functional synergy among the cloud super-brain, edge gateways, and mobile agents, while simultaneously supporting mobility adaptation, real-time responsiveness, and open interoperability. The core innovation of the cloud super-brain module lies in the construction of a global–local dual-layer digital twin model. Direct intervention in terminal-level execution is avoided; instead, high-level task objectives and constraints are generated using reinforcement learning algorithms. The state value function is defined as:

$$V(s_t) = E\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \middle| s_t\right] \tag{1}$$

where, $\gamma \in [0.9, 0.95]$ denotes the discount factor and r_{t+k} represents the immediate reward. Through iterative optimization of this function, global resource allocation rules and coordination policies are continuously refined. Meanwhile, digital twin model parameters are dynamically updated based on terminal operation data uploaded from the edge layer, thereby alleviating the mismatch between cloud-based models and real-world operations. In addition, lightweight communication protocols are adopted to reduce terminal data transmission overhead. The edge gateway layer, serving as the core hub for regional coordination, is equipped with lightweight digital twin replicas that are incrementally synchronized with the cloud layer, with synchronization latency maintained within 50 ms. Real-time coordination among terminals within a region is achieved using an improved distributed particle swarm optimization algorithm, whose optimization objective is expressed as:

$$\min J = \omega_1 T + \omega_2 E + \omega_3 C \tag{2}$$

where, ω_1, ω_2, and ω_3 denote the weighting coefficients, while T, E, and C represent task completion time, energy consumption, and conflict rate, respectively. By optimizing the time complexity to $O(n \log n)$, simultaneous access by hundreds of mobile devices is supported. A dual-mode communication architecture integrating 5G-U and LoRa is adopted to ensure communication stability in complex environments. When computationally intensive terminal tasks are offloaded to the edge, the offloading latency is maintained at no more than 20 ms, leading to a substantial reduction in terminal energy consumption. The embedded design of mobile agents is oriented toward lightweight and autonomous coordination capability. Multiple expert sub models with a total footprint not exceeding 50 MB are integrated, and an improved coalition formation game algorithm is embedded to enable peer-to-peer multi-issue negotiation, with negotiation convergence achieved within 300 ms. By fusing data from global positioning system/BeiDou positioning, inertial navigation, and vision sensors, centimeter-level localization accuracy is achieved. Operational and environmental states are continuously sensed and fed back to the digital twin models, providing data-driven support for adaptive decision-making.

3 KEY TECHNOLOGY IMPLEMENTATION AND ALGORITHM DESIGN

3.1 Multimodal mobile agent coordination algorithms

An improved coalition formation game algorithm is designed to address multi-issue negotiation requirements in mobile environments. The primary innovation lies in the construction of a triple-objective weighted utility function to support global optimization, while efficient coalition mechanisms and stability assurance strategies are incorporated to accommodate dynamic operating conditions. The utility function is defined as:

$$U_i = \alpha S_{iT} + \beta(1 - C_{iE}) + \gamma R_{iU} \quad (3)$$

where, α, β, and γ are normalized weighting coefficients, S_{iT} denotes time-window satisfaction, C_{iE} represents the unit-task energy consumption ratio, and R_{iU} indicates resource utilization efficiency. Through this formulation, multi-objective trade-offs are balanced, thereby preventing inefficiencies arising from single-dimension optimization. Coalition formation is realized using a greedy-pruning strategy, in which agents rapidly identify potential collaborators based on locally perceived information and form temporary coalitions. The pruning threshold is set to $\theta = 0.7$, and coalition reconfiguration time is strictly constrained to within 500 ms, enabling rapid responsiveness to dynamic order variations. In addition, a coalition stability penalty factor λ is introduced, imposing utility deductions on agents that withdraw prematurely from coalitions. As a result, coalition stability is significantly enhanced, yielding performance superior to that of conventional coalition formation algorithms.

A context-aware adaptive decision-making algorithm is further developed based on a lightweight knowledge graph and an improved similarity computation method, enabling rapid response. The core innovation is reflected in the coordinated design of graph compression and dynamic update mechanisms. After structured compression, the number of knowledge graph nodes is constrained to fewer than 1,000, retaining only essential entities and relationships relevant to logistics scenarios, thereby achieving a balance between lightweight representation and decision effectiveness. An improved cosine similarity algorithm is employed to compute the matching degree between real-time contexts and historical contexts, expressed as:

$$Sim = \frac{\sum_{k=1}^{n} w_k x_k y_k}{\sqrt{\sum_{k=1}^{n} w_k x_k^2}\sqrt{\sum_{k=1}^{n} w_k y_k^2}} \quad (4)$$

where, w_k denotes the weight of the contextual feature and is determined using an information gain–based method, thereby improving matching accuracy in complex scenarios. Decision response time is maintained within 100 ms. By integrating reinforcement learning, dynamic updates of the knowledge graph are realized, in which newly acquired decision experiences from emerging scenarios are incrementally incorporated into the graph. The update step size is set to $\eta = 0.01$, ensuring adaptive performance across heterogeneous logistics environments without the need for manual parameter tuning.

A dynamic expert agent invocation algorithm is developed to establish a distributed mechanism comprising demand triggering, dynamic networking, and task decomposition, thereby overcoming the computational redundancy inherent in conventional static invocation schemes. Trigger conditions are determined based on threshold evaluation of complex problem characteristics. When a mobile agent detects that fault severity levels or order surges exceed predefined thresholds, an invocation request is initiated through the edge gateway. During the networking phase, an improved shortest-path-first algorithm is employed, with the path cost function defined as:

$$Cost = d_{ij} \times (1 + \omega P_{ij}) \tag{5}$$

where, d_{ij} denotes the physical distance between the expert agent and the requesting node, P_{ij} represents communication link quality, and $\omega = 0.2$ is a weighting coefficient. Decision fusion is performed using a weighted voting scheme, in which weights are dynamically allocated according to the domain-specific accuracy of expert agents. The equation is expressed as:

$$W_m = \frac{Acc_m}{\sum_{m=1}^{n} Acc_m} \tag{6}$$

where, Acc_m denotes the historical decision accuracy of the m-th expert agent. Through this mechanism, overall decision accuracy is substantially improved compared with single-expert models, while terminal-side computational load is simultaneously reduced.

3.2 Mobile edge computing-empowered mobile coordination technologies

A dynamic task offloading strategy is developed with dual-objective optimization of latency and energy consumption as its core objective. An adaptive decision model is constructed based on the real-time states of mobile agents and the resource utilization of edge nodes, thereby overcoming the scenario-adaptation limitations inherent in conventional static offloading strategies. A binary particle swarm optimization algorithm is employed to determine the optimal offloading scheme, with the objective function defined as:

$$J = \omega_1 D + \omega_2 E \tag{7}$$

where, ω_1 and ω_2 denote normalized weighting coefficients, D represents end-to-end task execution latency, and E denotes local computational energy consumption of mobile agents. Through iterative updates of particle positions and velocities, optimal solutions are efficiently searched, ensuring that decisions simultaneously satisfy low-latency and low-power requirements in mobile environments. A load-balancing mechanism is deployed at the edge layer, in which central processing unit and memory utilization are continuously monitored in real time. When resource utilization exceeds a threshold of 70%, a task migration process is automatically triggered, and a portion of computational tasks is rescheduled to neighboring idle edge nodes to maintain the stability of offloading services. In parallel, computational tasks are encapsulated using Docker-based containerization, enabling rapid deployment and migration through standardized interfaces. As a result, customized development for heterogeneous mobile agent hardware architectures is avoided, and the generality of the proposed strategy is significantly enhanced.

Lightweight digital twin and real-time simulation technologies are extensively optimized to accommodate the resource-constrained characteristics of mobile environments. Through model compression and process restructuring, decision pre-evaluation and dynamic adaptation are enabled, providing reliable simulation support for mobile agents. Model lightweighting is achieved through a combined strategy of polygon simplification and texture compression. By removing redundant geometric surfaces and reducing texture resolution, the storage footprint of digital twin models is significantly reduced while preserving essential structural and functional characteristics. The compression ratio is defined as:

$$CR = \left(1 - \frac{V_C}{V_O}\right) \times 100\% \tag{8}$$

where, V_c denotes the compressed model volume and V_o represents the original model volume. A real-time simulation mechanism is established to form a closed-loop decision process comprising "solution generation–virtual pre-evaluation–optimal selection." After multiple candidate decision schemes are generated by mobile agents, the corresponding parameters are transmitted to lightweight digital twin replicas at the edge layer via edge gateways. Rapid simulation rollouts of 10–20 steps are then executed, and the optimal solution is selected based on simulation outcomes, thereby substantially reducing trial-and-error costs during physical execution. In the data synchronization phase, an incremental synchronization protocol is employed, in which only state-change data $\Delta S = S_t – S_{t-1}$ are transmitted, eliminating the need for full data transfer. This approach effectively accommodates bandwidth fluctuations in mobile environments and ensures state consistency between digital twin models and their corresponding physical entities.

3.3 Embedded technology implementation for mobile agents

The embedded hardware module of mobile agents is designed using a unified adaptation architecture for heterogeneous carriers, with the core innovation achieved through a highly integrated hardware framework and coordinated multimodal components. Real-time decision-making performance, precise perception capability, and communication stability in complex environments are jointly ensured. The core controller is implemented using an ARM Cortex-A76–based processor, with the clock frequency maintained above 2.4 GHz and support for eight-thread parallel processing. At the hardware level, a floating-point computation unit and a neural network acceleration module are integrated, with a single-instruction execution cycle not exceeding 1.2 ns, thereby satisfying the real-time computational requirements of lightweight expert algorithms and collaborative decision-making. The perception subsystem adopts a multi-source fusion design, integrating dual-mode global positioning system/BeiDou positioning units, an inertial measurement unit, high-definition cameras, and light detection and ranging sensors. Centimeter-level positioning accuracy is achieved, and parallel acquisition of multisensor signals is enabled through hardware-level data synchronization interfaces. The sampling frequency is set to 100 Hz, providing high-timeliness and high-precision data support for context awareness and adaptive decision-making. The communication module is equipped with a multi-mode chipset supporting 5G-U, LoRa, and Wi-Fi 6, with dynamic communication mode switching supported at the hardware level based on link quality. When 5G-U signals are obstructed, automatic switching to LoRa mode is performed to maintain low-rate communication, and rapid switching back to 5G-U is executed upon signal recovery. Through this mechanism, communication continuity is ensured during mobile operations.

The embedded software is designed using a layered architecture, with the core innovation reflected in precise latency control across layers and algorithm–hardware co-optimization, enabling an efficient closed loop encompassing perception, decision-making, and execution. The perception layer is responsible for multi-source data acquisition and preprocessing. An improved Kalman filtering algorithm is employed to suppress localization noise, with the core state update equation expressed as:

$$X_{k|k} = X_{k|k-1} + K_k(Z_k - HX_{k|k-1}) \tag{9}$$

where, K_k denotes the Kalman gain and H represents the observation matrix. By dynamically adjusting the gain coefficients, a balance between localization accuracy and computational overhead is achieved, while preprocessing latency is strictly constrained to within 10 ms. The decision layer adopts a lightweight design tailored to available hardware computing resources. Expert submodels and coordination algorithms are optimized at the instruction level to match the characteristics of the ARM instruction set. As a result, algorithm runtime memory consumption is maintained below 40 MB, ensuring rapid generation of execution commands under hardware resource constraints. The execution layer employs a hardware-interrupt–driven design and is directly interfaced with the mobile carrier control system. Command transmission is implemented through standardized interfaces, while execution states are simultaneously fed back to the decision layer in real time, forming a hardware-level closed loop of "perception–decision–execution." Through coordinated software–hardware optimization, mobile agents are capable of sustained autonomous operation for more than 4 hours under a rated power consumption of 15 W, thereby achieving a favorable balance between energy efficiency and operational stability.

4 CASE VALIDATION AND SIMULATION ANALYSIS

4.1 Overall experimental design

A four-dimensional quantitative evaluation framework was adopted. All experiments were independently repeated 30 times, and one-way analysis of variance was conducted using IBM SPSS Statistics 26.0, with the significance level set at 0.05. Experimental results were reported as mean ± standard deviation to mitigate the influence of random variation. The efficiency dimension included average order fulfillment time, mobile device utilization rate, and system throughput.

The coordination and mobility adaptability dimensions encompassed negotiation convergence time, task conflict resolution success rate, end-to-end decision latency, per-task energy consumption, and communication bandwidth utilization. The robustness dimension evaluated fault recovery time, order fluctuation adaptability coefficient, communication interruption recovery time, and task error rate under adversarial conditions. The scalability dimension was characterized by a performance degradation coefficient to assess system stability under increasing scale. In addition, three gradient comparative schemes were established. Scheme A represents a traditional centralized scheduling approach based on a control-tower paradigm, in which instructions are generated exclusively at the cloud layer, without edge-level coordination or autonomous agent negotiation, serving as the conventional technical baseline. Scheme B corresponds to a standard multi-agent approach, in which terminal-level autonomous decision-making is enabled within a basic multi-agent system architecture, but without the support of mobile edge computing, digital twin technology, or expert agents, representing the current application level. Scheme C implements the proposed framework, with full deployment of the core architectural innovations and technical modules, thereby highlighting the incremental performance gains.

The experiments were conducted on a co-simulation platform integrating AnyLogic and ROS, complemented by a heterogeneous hardware testbed. The simulation platform was configured with an Intel Xeon E5-2699 v4 processor and 64 GB of memory, enabling the construction of a high-fidelity digital twin environment. Network latency was emulated to reflect realistic 5G-U communication conditions, with a mean delay of 20 ms and a fluctuation range of ±5 ms, thereby reproducing a wide range of dynamic logistics operating scenarios. The hardware testbed consisted of heterogeneous mobile carriers, including automated guided vehicles, unmanned aerial vehicles, and augmented reality wearable devices, together with industrial-grade edge gateways and cloud servers. The system operated under Ubuntu 22.04 and a Docker-based containerized environment, ensuring compatibility with embedded algorithm execution, dual-mode communication testing, and hardware resource utilization assessment, thereby bridging the gap between purely simulated evaluation and real-world engineering deployment.

4.2 Baseline scenario simulation validation

Warehouse–distribution integrated automated guided vehicle dynamic coordination scenario. A warehouse–distribution environment comprising 50 automated guided vehicles and 10 loading/unloading docks was constructed. Three representative operating conditions were considered: normal order flow, order peak, and equipment failure. Under the order-peak condition, order volume was increased by 50% relative to the average level, while under the equipment-failure condition, 2–3 automated guided vehicles were randomly disabled. This scenario was designed to primarily evaluate the coordination and scheduling efficiency of mobile agents within a localized operational area. The experimental results are illustrated in Figure 2. The evaluated performance indicators included average order fulfillment time (min), task conflict resolution rate (%), end-to-end decision delay (ms), and communication bandwidth occupancy rate (%).

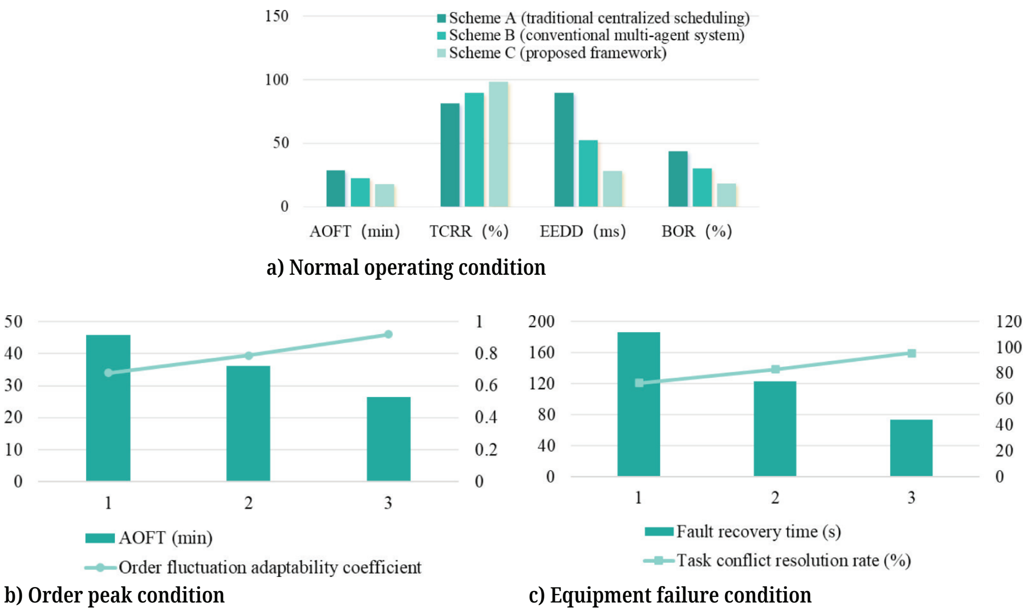

Fig. 2. Performance comparison in the warehouse–distribution integrated automated guided vehicle scenario

As shown in Figure 2, Scheme C demonstrates statistically significant performance advantages across all operating conditions. Under normal operating conditions, the average order fulfillment time is reduced by 38.2% compared with Scheme A and by 22.7% compared with Scheme B, while the task conflict resolution rate reaches 98.3 ± 1.1%. These improvements are primarily attributed to the synergistic effects of the edge-level dynamic coordination algorithms and the improved coalition formation game algorithm, through which automated guided vehicles are enabled to autonomously reorganize task sequences. As a result, command transmission delays inherent to centralized scheduling and negotiation redundancy associated with conventional multi-agent approaches are effectively mitigated. In terms of mobility adaptability, the end-to-end decision delay of Scheme C is limited to 28.3 ± 2.1 ms, corresponding to reductions of 68.4% and 46.3% relative to Schemes A and B, respectively. In addition, both per-task energy consumption and communication bandwidth occupancy rate are substantially optimized. These gains arise from the combined effects of the mobile edge computing-enabled task offloading strategy and the incremental data synchronization protocol, which collectively align with the core needs of mobile devices, including low power consumption and limited bandwidth availability. Under order peak and equipment failure conditions, the superiority of Scheme C becomes even more pronounced. The order fluctuation adaptability coefficient reaches 0.92 ± 0.03, and the fault recovery time is reduced by 60.2% compared with Scheme A. These results confirm the strong adaptability of the proposed framework to dynamic operating conditions, in which resource allocation can be rapidly adjusted through coordinated cloud-level global optimization and edge-level local responsiveness.

Urban last-mile unmanned aerial vehicle–automated guided vehicle hybrid delivery scenario. An urban delivery scenario covering a 30 km² metropolitan area was constructed, in which 20 unmanned aerial vehicles and 30 automated guided delivery vehicles were deployed. Four representative operating conditions were simulated: normal delivery, traffic congestion, temporary order insertion, and signal obstruction. Temporary order insertion accounted for 20% of total orders, while signal obstruction was modeled to reflect communication shielding effects caused by high-rise urban buildings. This scenario was designed to primarily evaluate cross-edge-node coordination and adaptability to complex mobile environments. The experimental results are presented in Figure 3.

With respect to cross-carrier coordination performance, under the temporary order insertion condition, the average order fulfillment time of Scheme C is reduced by 44.2% compared with Scheme A, while the negotiation convergence time is limited to 315 ± 17 ms, corresponding to a 49.4% reduction relative to Scheme B. These improvements are primarily attributed to the peer-to-peer negotiation mechanism of mobile agents and cross-carrier task allocation optimization at the edge gateway, through which task assignments between unmanned aerial vehicles and automated guided vehicles are rapidly adjusted, enabling efficient responses to urgent orders. In terms of communication stability and energy efficiency, under the signal obstruction condition, the communication interruption rate of Scheme C is maintained at 1.2 ± 0.5%, while per-task energy consumption is reduced by 32.4% compared with Scheme A. These gains are enabled by the dual-mode 5G-U/LoRa communication switching mechanism, which automatically switches to LoRa mode under signal blockage to maintain connectivity. In parallel, the expert agent–based energy optimization model dynamically adjusts device operating parameters, jointly ensuring communication robustness and low-power operation. Under traffic congestion conditions, the order fluctuation adaptability coefficient of Scheme C reaches 0.89 ± 0.04, significantly outperforming the comparative schemes. This result confirms that the context-aware perception capability of mobile agents effectively identifies complex environmental states and, when combined with lightweight digital twin–based simulation pre-evaluation, enables optimized route planning to avoid congested areas, thereby improving delivery efficiency.

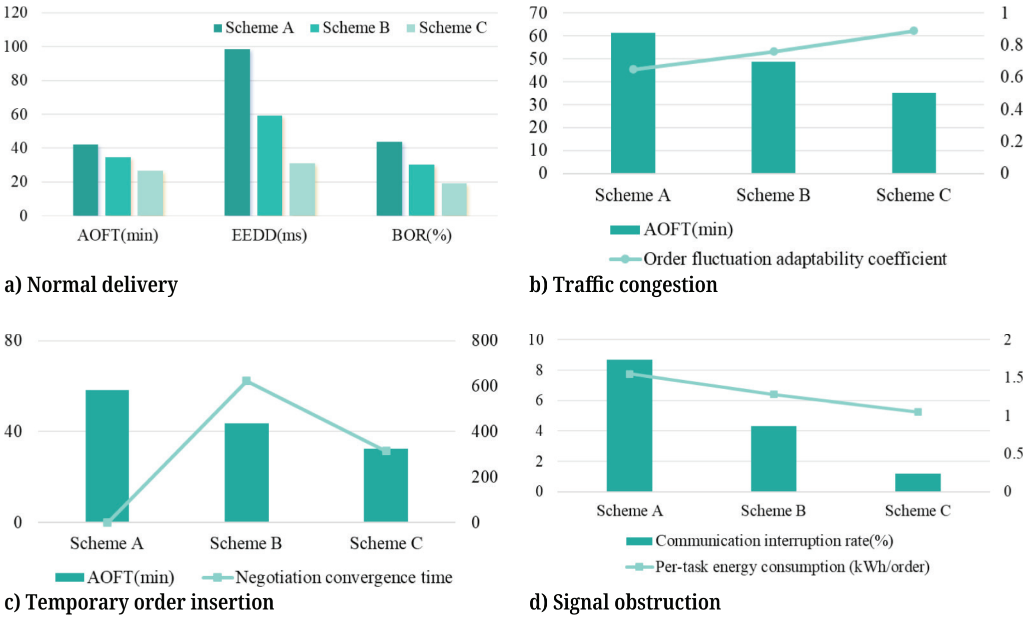

Fig. 3. Performance comparison in the urban last-mile scenario

4.3 Targeted validation of core innovative mechanisms

To quantify the performance contribution of individual innovations, single-variable controlled experiments were conducted, focusing on the dynamic expert agent invocation mechanism and the lightweight digital twin–based real-time simulation mechanism. Through this design, the technical gains of each core mechanism were explicitly quantified, ensuring that the innovative value is traceable and verifiable.

Table 1. Targeted validation results of the expert agent mechanism (mean ± standard deviation)

Comparison Group	Failure Resolution Time (s)	Decision Accuracy (%)	Hardware Load Rate (%)	P Value (vs. Dynamic Group)
Without expert agents	148 ± 9	82.3 ± 3.2	48.5 ± 2.6	<0.001
Static expert agents	104 ± 7	93.5 ± 2.1	62.8 ± 3.1	<0.001
Dynamic invocation mechanism	85 ± 5	96.7 ± 1.3	43.6 ± 2.2	–

A multi-device cooperative failure scenario was selected, in which automated guided vehicle battery depletion and unmanned aerial vehicle route conflicts occurred simultaneously, representing a complex operating condition. Three comparison groups were established: without expert agents, static expert agents, and dynamically invoked expert agents. In the static expert agent configuration, all expert modules were invoked simultaneously, whereas in the dynamic invocation configuration, domain-specific expert modules were activated on demand. The experimental results are summarized in Table 1.

As indicated in Table 1, the dynamic invocation mechanism reduces failure resolution time by 42.5% relative to the configuration without expert agents and by 27.8% relative to the static expert agent configuration. Decision accuracy reaches 96.7 ± 1.3%, representing an improvement of 3.4 percentage points over the static configuration. Meanwhile, the hardware load rate of the dynamic invocation group is limited to 43.6 ± 2.2%, corresponding to a 30.6% reduction compared with the static expert agent group. These advantages primarily arise from the on-demand activation of expert modules, which avoids the computational redundancy inherent in static invocation schemes. As a result, complex faults are resolved with high precision while terminal-side hardware load is substantially reduced. The experimental findings confirm that the dynamic expert agent invocation mechanism serves as a critical enabler for enhancing complex problem-solving capability and optimizing hardware resource utilization, effectively balancing decision accuracy and computational efficiency.

An automated guided vehicle path re-planning scenario was selected. Two comparison groups were established: without digital twin simulation and with real-time digital twin simulation. In the real-time simulation group, optimal decisions were executed after a 10–20-step pre-evaluation using lightweight digital twin replicas deployed at the edge layer, whereas in the non-simulation group, generated decision plans were executed directly without prior simulation. The experimental results are summarized in Table 2.

Table 2. Targeted validation results of the lightweight digital twin mechanism (mean ± standard deviation)

Comparison Group	Path Conflict Rate (%)	Task Completion Time (min)	Decision Trial-and-Error Cost (kWh)	P Value (Inter-Group Difference)
Without digital twin simulation	8.8 ± 1.5	19.6 ± 1.1	0.32 ± 0.04	<0.001
Real-time digital twin simulation	2.1 ± 0.8	15.8 ± 0.9	0.11 ± 0.02	<0.001

As shown in Table 2, the real-time digital twin simulation group exhibits a path conflict rate reduced to 2.1 ± 0.8%, corresponding to a 76.3% decrease relative to the non-simulation group. In addition, task completion time is shortened by 19.4%, while the decision trial-and-error cost is reduced by 65.6%. These advantages are attributed to the closed-loop mechanism of "simulation before execution," in which solution feasibility is evaluated through digital twin pre-evaluation prior to physical execution, thereby proactively avoiding path conflicts and related failures. As a result, decision trial-and-error costs and task delay risks are substantially mitigated. Meanwhile, the lightweight design ensures that simulation latency is maintained within 50 ms, without introducing additional decision delays. These findings demonstrate that the mechanism represents a key enabling technology for enhancing the action reliability of mobile agents and improving adaptability to dynamic operating environments.

4.4 Robustness against interference and security performance in complex environments

To address key challenges inherent to mobile technologies, robustness was evaluated along two critical dimensions—communication anti-interference capability and data security performance—under adverse communication conditions and malicious attacks. This evaluation aligns with the core concerns of mobile-technology-oriented journals regarding communication stability and data protection. The experimental results are summarized in Table 3.

Table 3. Comparison of anti-interference and security performance in complex environments (mean ± standard deviation)

Operating Condition	Evaluation Metric	Scheme A (Traditional Centralized)	Scheme B (Conventional Multi-Agent System)	Scheme C (Proposed Framework)	P Value (Inter-Group Difference)
Weak network	Communication interruption recovery time (ms)	1200 ± 85	850 ± 62	480 ± 41	<0.001
Network outage	Offline decision task completion rate (%)	68.5 ± 3.4	80.7 ± 2.8	92.3 ± 2.1	<0.001
Data eavesdropping attack	Task error rate (%)	12.3 ± 1.8	8.5 ± 1.3	3.2 ± 0.7	<0.001
	Data leakage defense success rate (%)	82.5 ± 3.1	88.7 ± 2.4	99.2 ± 0.6	<0.001
Command tampering attack	Task error rate (%)	15.6 ± 2.1	10.2 ± 1.5	3.5 ± 0.9	<0.001

In terms of communication anti-interference performance, under weak-network conditions, the communication interruption recovery time of Scheme C is maintained at ≤ 500 ms, representing reductions of 59.2% and 43.5% relative to Schemes A and B, respectively. Under network-outage conditions, the offline decision task completion rate reaches 92.3 ± 2.1%, significantly outperforming the comparative schemes. These results are attributed to the dual-mode communication switching mechanism and the edge-level autonomous coordination mode, through which communication modes are adaptively switched and edge-side resources are leveraged to sustain task execution during network anomalies, thereby ensuring communication continuity and operational stability. From the perspective of data security performance, under data eavesdropping and command tampering attacks, the task error rate of Scheme C remains below 3.5%, while the data leakage defense success rate reaches 99.2%. These outcomes are primarily enabled by lightweight encryption mechanisms and hash-based integrity verification, which provide effective security protection with minimal bandwidth overhead. As a result, the security requirements of logistics data transmission are satisfied, further confirming the robustness of the proposed framework in complex mobile environments.

5 CONCLUSION AND OUTLOOK

In response to the persistent challenges of delayed responsiveness and inefficient coordination in logistics collaboration under dynamic environments, a comprehensive investigation was conducted with a focus on the deep integration of mobile agents and logistics scenarios. Through architectural innovation, mechanism design, and technological integration, a digital twin–driven cloud–edge–end collaborative mobile agent management framework was established, forming a complete approach to logistics coordination management. The main contributions are manifested across three dimensions. At the architectural level, a hierarchically decoupled collaborative ecosystem is proposed, in which functional differentiation among the cloud, edge, and terminal layers enables a dynamic balance between global optimization and local real-time responsiveness, thereby addressing the insufficient mobility adaptation inherent in traditional architectures. At the mechanism level, a multimodal coordination mechanism is developed by integrating improved game-theoretic algorithms with context-aware technologies, overcoming critical bottlenecks related to real-time negotiation and dynamic task reconfiguration on mobile devices. At the technological level, deep integration of mobile edge computing, lightweight digital twin technology, and mobile agents is achieved, significantly enhancing real-time performance and energy efficiency in mobile environments. Extensive multi-scenario experiments demonstrate that the proposed framework consistently outperformed existing approaches, providing strong support for large-scale practical deployment. Despite these advances, several challenges remain in real-world implementation. Security risks associated with wireless communication links persist, the adaptation cost for heterogeneous mobile devices remains high, and the absence of unified industry standards continues to constrain large-scale industrial adoption. These issues are expected to be progressively addressed through closer integration with engineering practice.

6 REFERENCES

[1] Q. Gao, G. U. Fu, L. Li, and J. Guo, "A framework of cloud-edge collaborated digital twin for flexible job shop scheduling with conflict-free routing," *Robotics and Computer-Integrated Manufacturing*, vol. 86, p. 102672, 2024. https://doi.org/10.1016/j.rcim.2023.102672

[2] M. A. S. Mustafa, "Predictive reliability-driven optimization of spare parts management in aircraft fleets using AI, IoT, and digital twin technologies," *Journal of Engineering Management and Systems Engineering*, vol. 4, no. 3, pp. 218–236, 2025. https://doi.org/10.56578/jemse040305

[3] W. Mao *et al.*, "E-CARGO-based dynamic weight offload strategy with resource contention mitigation for edge networks," *Journal of Industrial Information Integration*, vol. 42, p. 100695, 2024. https://doi.org/10.1016/j.jii.2024.100695

[4] G. Peng, Y. Wen, W. Dou, T. Li, X. Xu, and Q. Ye, "Edge intelligence empowered delivery route planning for handling changes in uncertain supply chain environment," *Journal of Cloud Computing*, vol. 13, no. 1, p. 69, 2024. https://doi.org/10.1186/s13677-024-00613-z

[5] P. Thipphayasaeng, P. Piriyasurawong, and S. Phanichsiti, "Digital twins-based cognitive apprenticeship model in smart agriculture," *International Journal of Interactive Mobile Technologies*, vol. 18, no. 12, pp. 72–84, 2024. https://doi.org/10.3991/ijim.v18i12.46847

[6] D. Soni and N. Kumar, "Machine learning techniques in emerging cloud computing integrated paradigms: A survey and taxonomy," *Journal of Network and Computer Applications*, vol. 205, p. 103419, 2022. https://doi.org/10.1016/j.jnca.2022.103419

[7] M. Johnston and E. Modiano, "Wireless scheduling with delayed CSI: When distributed outperforms centralized," *IEEE Transactions on Mobile Computing*, vol. 17, no. 11, pp. 2703–2715, 2018. https://doi.org/10.1109/TMC.2018.2809739

[8] K. Christodoulopoulos, V. Sourlas, I. Mpakolas, and E. Varvarigos, "A comparison of centralized and distributed meta-scheduling architectures for computation and communication tasks in Grid networks," *Computer Communications*, vol. 32, nos. 7–10, pp. 1172–1184, 2009. https://doi.org/10.1016/j.comcom.2009.03.004

[9] A. I. Corréa, A. Langevin, and L. M. Rousseau, "Scheduling and routing of automated guided vehicles: A hybrid approach," *Computers & Operations Research*, vol. 34, no. 6, pp. 1688–1707, 2007. https://doi.org/10.1016/j.cor.2005.07.004

[10] M. Serror, S. Hack, M. Henze, M. Schuba, and K. Wehrle, "Challenges and opportunities in securing the industrial Internet of Things," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 2985–2996, 2020. https://doi.org/10.1109/TII.2020.3023507

[11] D. Serpanos, "Industrial Internet of Things: Trends and challenges," *Computer*, vol. 57, no. 1, pp. 124–128, 2024. https://doi.org/10.1109/MC.2023.3331552

[12] D. L. Cruz and W. Yu, "Path planning of multi-agent systems in unknown environment with neural kernel smoothing and reinforcement learning," *Neurocomputing*, vol. 233, pp. 34–42, 2017. https://doi.org/10.1016/j.neucom.2016.08.108

[13] G. Stagg and C. K. Peterson, "Multi-agent path planning for level set estimation using B-splines and differential flatness," *IEEE Robotics and Automation Letters*, vol. 9, no. 5, pp. 4758–4765, 2024. https://doi.org/10.1109/LRA.2024.3384763

[14] I. Al-Hammadi, M. Li, S. M. Islam, and E. Al-Mosharea, "Collaborative computation offloading for scheduling emergency tasks in SDN-based mobile edge computing networks," *Computer Networks*, vol. 238, p. 110101, 2024. https://doi.org/10.1016/j.comnet.2023.110101

[15] S. Zemlyak, I. Nozdreva, and S. Sivakova, "Implementation of AI in smart logistics based on mobile technologies," *International Journal of Interactive Mobile Technologies*, vol. 18, no. 17, pp. 88–100, 2024. https://doi.org/10.3991/ijim.v18i17.50735

7 AUTHOR

Yong Chen earned a Ph.D. degree in Management Science and Engineering from Wuhan University of Technology, she is currently affiliated with Shangqiu Polytechnic. Her research focuses primarily on logistics management (E-mail: 13507699675@163.com).