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Autonomous Mobile Robots for Smart Warehouse Logistics Optimization

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Abstract

This study investigates the optimization of smart warehouse logistics using autonomous mobile robots (AMRs) and proposes an integrated framework for improving order fulfillment, routing efficiency, and warehouse throughput. The proposed framework combines sensor-based autonomous navigation, a warehouse management system, fleet coordination, reinforcement-learning-based task allocation, dynamic path planning, and energy-aware scheduling. A simulated warehouse comprising 1,000 storage locations and 50 AMRs is used for performance evaluation. Compared with manual warehouse operations, the proposed AMR system reduces average order fulfillment time from 18.4 to 11.2 min (39.1% reduction) and increases throughput from 320 to 470 orders/hour (a 46.9% increase). Furthermore, worker travel distance decreases by 67.3%, while operational cost decreases by 34.4%. The results demonstrate that coordinated AMR deployment can significantly improve warehouse productivity, operational flexibility, and resource utilization, supporting the development of intelligent Industry 4.0 logistics systems.

Keywords: Autonomous mobile robots; smart warehouse; logistics optimization; path planning; fleet management

1. Introduction

Modern supply chains increasingly rely on highly efficient warehouse operations to meet the growing demand generated by global e-commerce and just-in-time distribution systems. Traditional warehouse operations often depend on manual labor or fixed automation systems such as conveyors and automated guided vehicles (AGVs). Although these systems have improved productivity, they lack the flexibility and scalability required for dynamic logistics environments.

Autonomous mobile robots (AMRs) represent a new generation of warehouse automation technologies capable of navigating independently within warehouse facilities using advanced sensing, mapping, and artificial intelligence (AI) algorithms. Unlike AGVs that rely on predefined paths such as magnetic strips or floor markers, AMRs can dynamically plan routes using simultaneous localization and mapping (SLAM) techniques and onboard sensors [1]. This capability allows them to adapt to changing warehouse layouts, obstacles, and operational conditions.

New breakthroughs in robotics, AI, and cyber-physical systems have contributed to the use of AMRs in logistic settings. The AMR technology is capable of moving products, supporting order picking activities, and coordinating with warehouse management systems (WMSs) for better optimization and reduction in inefficiencies [2]. Logistics and retail firms have begun utilizing robotic warehouses to enhance their throughput capacity and increase inventory precision. As depicted in Fig. 1, the conceptual model of a warehouse logistics system utilizing AMRs with the WMS and intelligent logistics system is presented. The warehouse includes storage racks, pick locations, pack locations, and charging points for the AMRs.

At the operational level, AMRs interact with the fleet management system (FMS), which coordinates robots, schedules tasks, and manages traffic. FMS gets task orders from the WMS, which controls inventory databases, order processing, and warehouse management. When an order arrives, the system dynamically allocates AMRs to move inventory containers or

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pallets from their respective storage spots to the picking stations. There is also a data analytics and optimization module in the cloud that enhances the logistics process by analyzing the operational data.

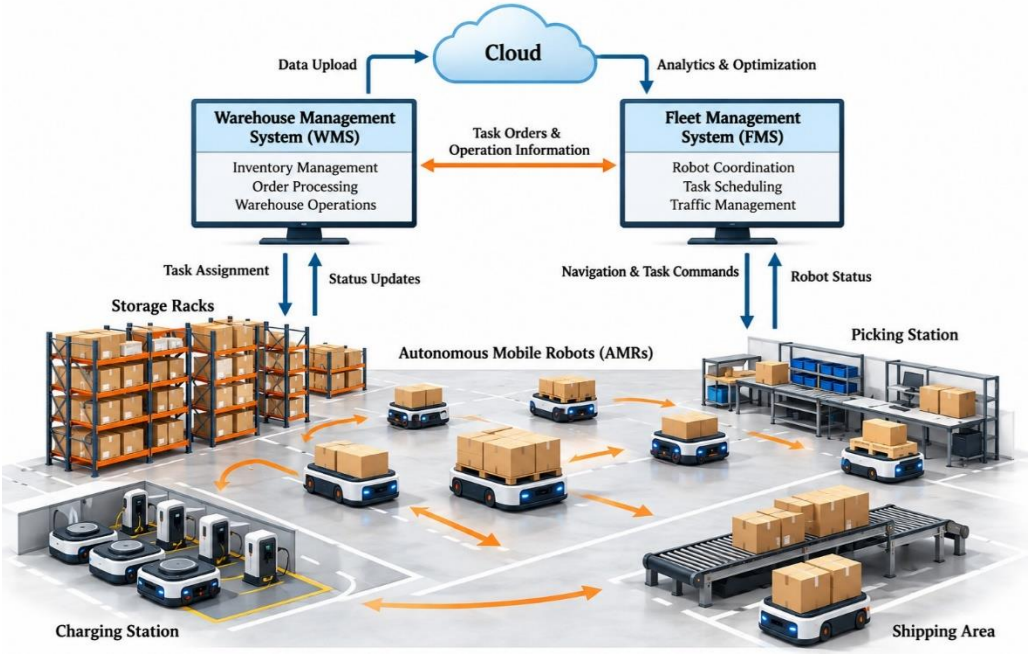


Fig. 1 Smart warehouse logistics system with AMRs

Overall, the architecture of a smart warehouse shows how cyber-physical systems, robotics, and AI technology work together to deliver high-efficiency logistical infrastructures. AMR-enabled warehouses make it possible to achieve higher levels of efficiency in terms of lower costs, shorter distances traveled, and shorter order delivery times. Thus, such warehouses have become a vital component of the latest Industry 4.0 logistical systems. Table 1 presents a comparison of important technologies that are utilized in warehouse automation in today's logistical settings. Manual warehouse technology relies heavily on human labor and works perfectly for small-scale logistics; however, this system cannot be considered highly productive because of its many errors. Conveyor technology is more efficient than manual systems in terms of higher throughput; however, it lacks flexibility due to fixed assets.

Table 1 Comparison of warehouse automation technologies

Automation technology	Navigation / Control method	Operational flexibility	Infrastructure requirement	Typical applications	advantages
Manual warehouse operations	Human operators using forklifts and carts	High	Very low	Small warehouses, low-volume logistics	Low initial investment, adaptable to layout changes
Conveyor-based automation	Fixed conveyor belts and sorting mechanisms	Low	Very high	Parcel sorting centers, manufacturing lines	High throughput for repetitive tasks
AGVs	Magnetic tape, QR markers, or laser guidance	Medium	Medium–high	Manufacturing material transport, structured warehouses	Reliable navigation and predictable routes
AMRs	AI-based navigation using LiDAR, cameras, and SLAM algorithms	Very high	Low	Smart warehouses, e-commerce logistics, fulfillment centers	Dynamic routing, flexible deployment, scalable robot fleets
Robotic shuttle systems	Rail-guided robotic shuttles within rack structures	Medium	High	High-density automated storage and retrieval systems (AS/RS)	Extremely high storage density and retrieval speed

Despite the growing adoption of AMRs in warehouse logistics, several limitations remain in existing studies. Previous research has frequently investigated autonomous navigation, path planning, task allocation, fleet coordination, and warehouse management integration as separate optimization problems. Comparatively limited attention has been given to an integrated framework that simultaneously coordinates robot navigation, intelligent task allocation, warehouse information management, congestion control, and energy-aware operation. Moreover, the combined influence of these functions on order fulfillment time, throughput, travel distance, operational cost, and robot utilization requires further quantitative investigation.

Therefore, this study aims to develop and evaluate an integrated AMR-based smart warehouse logistics optimization framework combining sensor-based navigation, WMS integration, fleet management, reinforcement-learning-based task allocation, dynamic path planning, multi-agent coordination, and energy-aware scheduling.

The novelty of this study lies not in introducing an individual AMR technology, but in developing a unified operational framework in which reinforcement-learning-based task allocation, dynamic route planning, multi-agent traffic coordination, WMS/FMS information exchange, and energy-aware scheduling interact within a common decision architecture.

The principal contributions of this study are fourfold. First, an integrated four-layer AMR warehouse architecture is developed to connect physical robots, fleet control, warehouse information, and AI-based optimization. Second, a dynamic task-allocation mechanism is combined with real-time route planning and congestion-aware multi-agent coordination to jointly improve task assignment and robot movement. Third, battery state is incorporated into operational scheduling to reduce charging-related interruption of warehouse activities. Fourth, the framework is quantitatively evaluated using multiple operational indicators, including order-fulfillment time, throughput, travel distance, picking accuracy, operational cost, robot utilization, and energy consumption. These contributions provide a system-level approach for studying the interaction among AMR control, warehouse information management, and logistics optimization.

The remainder of this paper is organized as follows. Section 2 reviews related studies on AMR-based warehouse logistics. Section 3 describes the proposed architecture and optimization methodology. Section 4 presents the experimental setup. Section 5 discusses the simulation results and performance comparison, while Section 6 summarizes the conclusions and future research directions.

2. Literature Review

Research on warehouse automation has gained increasing attention owing to the development of intelligent robotic systems. The early development of automated warehouses involved the utilization of AGVs that would traverse predetermined paths with the help of guidance equipment like magnets or laser tags [3]. Although AGVs provided improved material handling capabilities, their dependency on infrastructure made them inflexible in changing conditions.

Recent developments have seen the introduction of AMRs, which use their sensors along with LiDAR and computer vision to navigate autonomously and avoid obstacles. The use of AMRs allows for decentralized decision-making where robots can communicate with other machines within the warehouse facility.

The literature review suggests that AMRs considerably enhance the productivity of the warehouse by decreasing the human walking distances in case of order picking tasks. Picker-to-part AMR solutions have been reported as being effective concerning order fulfillment process efficiency as well as the throughput rate [5]. The use of an AMR fleet with CPS and DT technologies allows warehouse operators to control the logistics processes in real time and perform logistics operation optimization [6].

Current scientific efforts focus on multi-robot cooperation algorithms, energy-efficient paths for robot movement, and FMSs based on AI. Such approaches seek to improve scalability, avoid traffic jams in robot networks, and optimize the design of warehouses [7-8]. However, several challenges remain in large-scale coordination, human-robot interaction safety, and incorporation into existing WMSs. Table 2 gives a summary of important research works on AMRs in warehouses. According to existing literature, AMRs enhance warehouse productivity through autonomous navigation and intelligent routing.

Table 2 Summary of research on AMRs in warehouse logistics

Reference	Research focus	Technology / Method	Key contributions	Limitations identified
Fragapane et al. (2021) [1]	Planning and control of AMRs in intralogistics	Operations research, fleet planning and control	Reviewed AMR planning and control strategies and identified research opportunities	Further investigation needed for integrated, real-time fleet optimization
Wesselhöft et al. (2022) [3]	Reinforcement-learning-based AMR fleet control	Reinforcement learning and fleet management	Surveyed reinforcement learning approaches for controlling AMR fleets	Scalability and practical deployment require further evaluation
Lackner et al. (2024) [4]	State-of-the-art AMR systems in intralogistics	Literature review and technology assessment	Examined AMR technologies, limitations, and research gaps	Real-world integration and deployment challenges remain
Turhanlar et al. (2024) [5]	Collision and deadlock prevention in warehouses	Agent-based modelling and collision-prevention algorithms	Investigated robot travel under collision and deadlock prevention strategies	Performance may depend on warehouse configuration and traffic conditions
Zhang and Abellera (2025) [6]	Smart warehouse automation and inventory management	Cyber-physical systems and AMR integration	Examined AMR integration with intelligent warehouse inventory management	Integration complexity and infrastructure requirements
Benavides-Robles et al. (2024) [7]	Robotic mobile fulfillment systems	Systematic literature review	Synthesized developments in robotic mobile fulfillment systems	Further investigation needed into coordinated optimization and operational scalability

2.1 Research gap and motivation

Existing AMR warehouse research has established important advances in autonomous navigation, robotic mobile fulfillment, task allocation, collision avoidance, and warehouse-system integration. Nevertheless, three research gaps remain relevant to this study. First, many approaches optimize individual functions, such as routing or task assignment, whereas fewer studies investigate their coordinated operation with WMS/FMS information exchange and energy management. Consequently, improvements obtained at one control level may not necessarily produce system-level improvements when congestion, battery constraints, order variability, and competing robot tasks are considered simultaneously.

Second, reinforcement-learning-based fleet control provides an adaptive alternative to fixed dispatching rules, but its integration with dynamic path planning and multi-agent traffic coordination requires clearer system-level investigation. In particular, task decisions should account not only for travel distance but also for robot availability, congestion, task urgency, and battery condition.

Third, the literature indicates continuing challenges in scalability, dynamic obstacle handling, communication reliability, sensor uncertainty, charging coordination, and deployment under real warehouse conditions. These limitations motivate an integrated AMR optimization architecture that coordinates task assignment, navigation, traffic management, WMS information, and energy-aware operation while evaluating their combined influence on warehouse-level performance.

Accordingly, this study investigates whether such integration can reduce fulfillment time and unnecessary movement while improving throughput, resource utilization, and operational efficiency. The framework is evaluated in a simulated warehouse environment, and its conclusions are therefore restricted to the investigated simulation conditions rather than interpreted as universal performance guarantees for physical warehouses.

3. Methodology

The proposed research framework introduces an AMR-based smart warehouse optimization model integrating robotics, AI, and WMSs. Fig. 2 presents the architecture of the proposed AMR-based smart warehouse system, which integrates robotics, AI, and warehouse information systems into a unified logistics optimization framework. The architecture is organized into four functional layers.

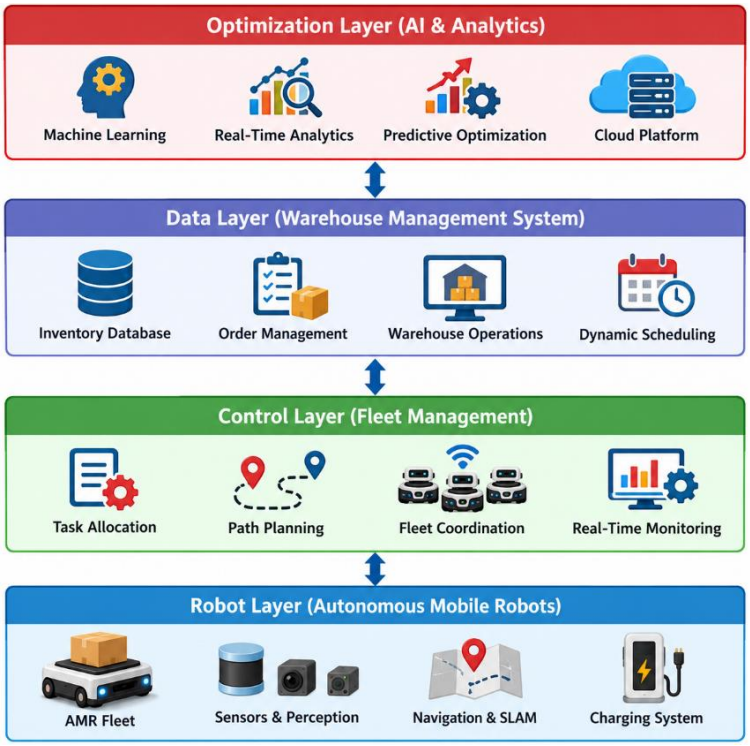


Fig. 2 Architecture of the proposed AMR-based smart warehouse system

3.1 System architecture

The system consists of four primary layers:

Robot layer (physical layer): this layer consists of AMRs operating within the warehouse environment. Each robot is equipped with sensors such as LiDAR, cameras, ultrasonic sensors, and inertial measurement units (IMU) for environment perception. These sensors enable robots to perform SLAM, obstacle detection, and autonomous navigation.

Control layer (fleet management layer): the FMS coordinates robot operations, including task scheduling, path planning, traffic management, and collision avoidance. Advanced routing algorithms and multi-agent coordination strategies ensure efficient robot movement within the warehouse.

Data layer (warehouse management layer): the WMS stores and processes operational data such as inventory records, order information, storage locations, and shipment schedules. The WMS communicates with the FMS to assign tasks to robots and monitor warehouse activities.

Optimization layer (AI analytics layer): the optimization layer uses machine learning algorithms and real-time data analytics to improve warehouse efficiency. AI models analyze logistics data to optimize robot routing, predict demand patterns, and reduce operational delays.

The architecture demonstrates how cyber-physical systems, cloud computing, and robotics technologies collaborate to create an intelligent logistics environment. Real-time communication between the layers enables dynamic decision-making and continuous optimization of warehouse operations. This layered architecture supports scalability, flexibility, and efficient logistics management, making it suitable for modern Industry 4.0 smart warehouse systems.

3.2 Optimization model

The optimization objective is to minimize total order fulfillment time:

$$\min J = a_1 T_{travel} + a_2 T_{queue} + a_3 T_{retrieval} + a_4 E_{AMR} + a_5 C_{Congestion} + a_6 P_{delay} \tag{1}$$

where J is the overall warehouse optimization objective, $\hat{T}_{\text{travel}}$ represents total AMR travel time, $\hat{T}_{\text{retrieval}}$ represents item retrieval time, and T_{queue} represents queue or congestion delays, $\hat{E}_{AMR}$ is total AMR energy consumption, $\hat{C}_{Congestion}$ is congestion penalty, $\hat{P}_{delay}$ is task-delay penalty, a_k is a nonnegative objective weighting coefficient (k =1, …, 6).; Subject to task assignment, robot capacity, collision avoidance, battery, and task-completion constraints. Eq. (1) minimizes the combined operational penalties associated with travel, waiting, retrieval, energy use, congestion, and task delays.

$$\sum_{i=1}^{N} x_{ij} = 1, \forall j \in \mathfrak{J} \tag{2}$$

where I is the set of AMRs, $\mathfrak{J}$ is the set of warehouse tasks, i is the AMR index, $i \in I$, j is task index, $j \in J$, x_{ij} is binary assignment decision variable.

The binary variable is defined as:

$$x_{ij} = \begin{cases} 1, \text{if AMR } i \text{ is assigned task } j \\ 0, \text{otherwise} \end{cases} \tag{3}$$

Eq. (2) ensures that every warehouse task is assigned to exactly one AMR. This is appropriate for tasks that require one robot; cooperative multi-robot tasks would require a different constraint.

$$L_j x_{ij} \le Q_t^{cap}, \forall \in I, j \in \mathfrak{J} \tag{4}$$

where Lj payload required by task j in kg, Q_i^{cap} is maximum payload capacity of AMR i in kg, x_{ij} is binary task-assignment variable defined in Eq. (3). Eq. (4) prevents a task from being assigned to an AMR whose maximum payload capacity is lower than the task's required payload. It assumes each robot's assigned load is evaluated one task at a time. Simultaneous multi-task loads require a cumulative capacity constraint.

$$b_i^{post}(t) \ge b_{\min}, \forall_i \in I_{assigned}(t) \tag{5}$$

where $b_i^{post}(t)$ is predicted battery state of charge of AMR i after its assigned task, b_{min} is minimum permissible battery state of charge, t is decision time, $I_{assigned}(t)$ is set of AMRs assigned tasks at time t. Both battery quantities are dimensionless fractions between 0 and 1. Eq. (5) ensures that an AMR is assigned a task only if its predicted remaining battery level after completing the task meets the minimum safety threshold. This supports energy-aware scheduling and helps prevent robot interruptions during warehouse operations.

The new algorithm consists of dynamic task allocation through reinforcement learning, real-time route planning via A* searches, collision avoidance through multi-agent coordination algorithms, and energy-aware scheduling for battery management. A simulation experiment was carried out with a digital warehouse having 50 robots and 1,000 storage slots.

3.3 Reinforcement-learning-based dynamic task allocation

The task-allocation problem is formulated as a sequential decision-making process in which the fleet controller acts as the decision agent. At decision epoch t, the state vector contains information describing robot position, availability, remaining battery state, current task queue, estimated travel distance, congestion condition, and task priority:

$$s_t = \left\{ \mathrm{P}_t,\ \mathrm{A}_t,\ \mathrm{B}_t,\ \mathrm{D}_t^{task},\ \mathfrak{A}_t,\ \mathrm{C}_t,\ \pi_{tj} \right\} \tag{6}$$

where s_t refers to warehouse system state at decision time t, P_t is the collection of AMR positions, A_t is the collection of AMR availability indicators, B_t is the collection of AMR battery states, D_t^{task} is the matrix of estimated AMR-to-task distances, $\mathfrak{A}_t$ is the current queue of pending warehouse tasks, C_t is the collection of local congestion measurements, and π_t is the collection of task priorities. Eq. (6) represents the information available to the reinforcement-learning controller when determining which AMR should perform a warehouse task. It includes robot availability, distance, battery level, congestion, and task priority.

The reward function penalizes task-completion time, unnecessary travel, congestion, and energy consumption while rewarding successful and timely task completion:

$$r_t = -\left(\omega_1 T_t + \omega_2 D_t + \omega_3 E_t + \omega_4 C_t + \omega_5 P_t \right) \tag{7}$$

where r_t is an immediate reinforcement-learning reward, T_t is task completion-time metric during decision interval t, $\hat{D}_t$ is total AMR travel distance during the interval, $\hat{E}_t$ is total AMR energy consumption during the interval, $\hat{C}_t$ is fleet congestion penalty during the interval, $\hat{P}_t$ is task lateness penalty during the interval, ω_k is nonnegative reward weight (k= 1,…, 5). Eq. (7) provides negative rewards for longer completion times, unnecessary travel, higher energy consumption, congestion, and task lateness. Maximizing cumulative reward therefore encourages more efficient fleet operation. The reward coefficients ω_k are separate from the objective coefficients a_k in Eq. (1).

Through repeated interaction with the simulated warehouse, the policy learns task-assignment decisions that minimize cumulative operational penalties while maintaining feasible robot operation.

The system's performance was measured in terms of the following parameters: completion time of an order, travel distance covered by robots, productivity of the warehouse, and energy consumed, illustrated in Fig. 3. Such performance measures can be used in the comparison of the traditional warehouse operation and the proposed AMR-based logistics optimization approach. The major features of the AMR-based warehouse optimization system developed in this study are presented in Table 3 with regard to the layered system architecture described in the methodology part.

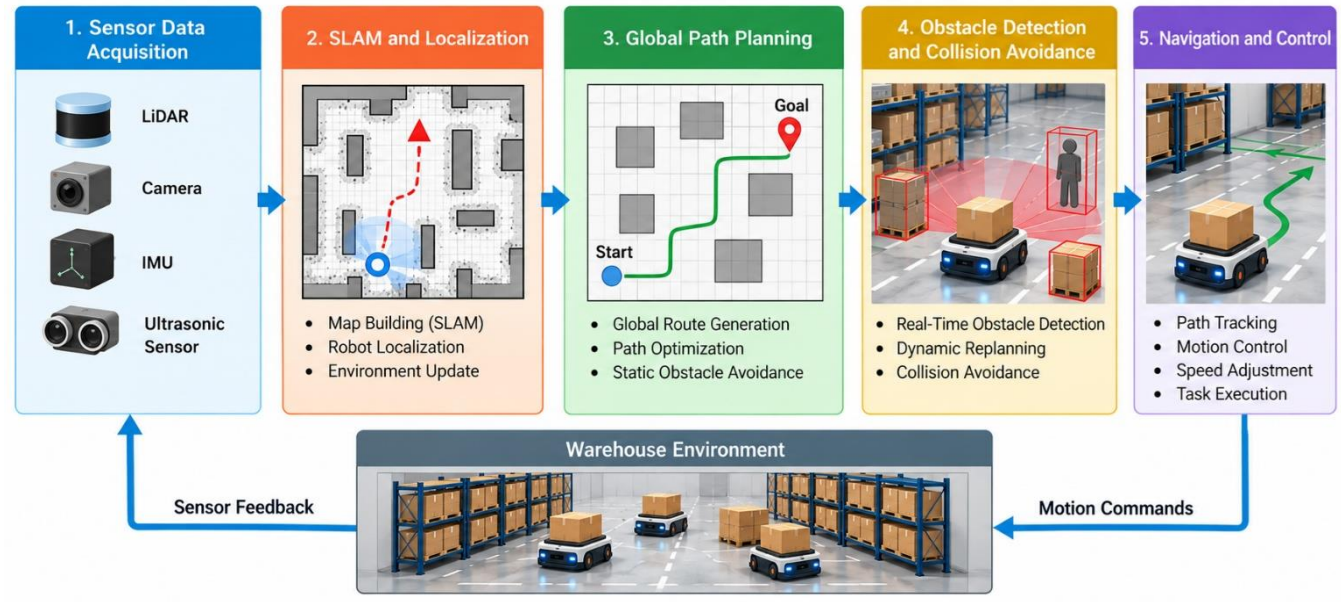


Fig. 3 Autonomous robot navigation and path planning workflow

Table 3 Components of the proposed AMR warehouse optimization system

Component	System layer	Technology/Tools	Primary function	Role in warehouse optimization
AMRs	Robot layer	LiDAR sensors, cameras, IMU, SLAM algorithms	Transport goods between storage locations, picking stations, and shipping areas	Reduce human labor and improve material handling efficiency
Robot navigation system	Robot layer	SLAM navigation, obstacle detection, localization algorithms	Enable autonomous movement and dynamic route planning	Minimize travel distance and avoid collisions
FMS	Control layer	Multi-agent coordination algorithms, task scheduling systems	Coordinate robot tasks, manage fleet operations, and monitor robot status	Improve logistics throughput and robot utilization
Path planning module	Control layer	A* algorithm, Dijkstra algorithm, reinforcement learning	Determine optimal routes for robots in real time	Reduce congestion and optimize robot movement
WMS	Data layer	Inventory databases, order management software	Manage inventory records, order processing, and warehouse operations	Synchronize logistics tasks and improve order fulfillment
Data analytics platform	Optimization layer	Big data analytics, machine learning models	Analyze warehouse operational data and performance metrics	Support predictive optimization and decision-making
Cloud computing infrastructure	Optimization layer	Cloud servers, distributed computing platforms	Store warehouse data and support large-scale computation	Enable real-time system monitoring and scalable operations
Energy management module	Optimization layer	Battery monitoring systems, charging algorithms	Monitor robot battery levels and schedule charging operations	Ensure continuous robot operation and energy efficiency

4. Experimental Setup

The proposed AMR-based warehouse optimization framework was evaluated using a simulated smart warehouse environment designed to reproduce typical order-picking, material-transport, and inventory-handling operations. The simulated warehouse consisted of 1,000 storage locations and a fleet of 50 AMRs. Each AMR was modeled with LiDAR, camera, IMU, and localization capabilities to support environmental perception, SLAM, obstacle detection, and autonomous navigation. The robots communicated with the FMS, while inventory information, order requests, storage locations, and shipment schedules were supplied through the WMS [9-10].

4.1 Simulation environment and warehouse configuration

The simulated warehouse was organized into storage, picking, shipping, robot-travel, and charging zones. Storage locations represent the origins of material-retrieval tasks, whereas picking and shipping stations represent the primary destinations. A connected aisle network enables AMRs to move between these functional areas. The simulation is designed to reproduce operational interactions including simultaneous robot movement, competing task requests, route intersections, aisle congestion, charging requirements, and dynamically generated orders.

At the beginning of an experimental run, robots are initialized at predefined or randomly assigned available positions according to the simulation configuration, as shown in Table 4. Customer orders are subsequently generated and transmitted through the WMS to the FMS. Each order generates one or more material-handling tasks requiring an AMR to travel from its current position to the corresponding storage location and subsequently to a picking or shipping destination.

Table 4 Configuration of the simulated smart warehouse

Parameter	Experimental configuration	Function
Storage locations	1,000	Represent warehouse inventory locations
AMR fleet size	50 robots	Material transport and order fulfillment
Warehouse zones	Storage, picking, shipping, charging	Functional logistics areas
Navigation environment	Connected aisle network	AMR movement and routing
Localization	SLAM-based	Robot localization and mapping
Primary sensors	LiDAR, camera, IMU	Perception and navigation
Fleet controller	FMS	Task allocation, routing and coordination
Information system	WMS	Inventory and order management
Path-planning method	A* + dynamic route adjustment	Route optimization
Task allocation	Reinforcement-learning based	Dynamic robot-task assignment

4.2 AMR Operational Model

Each simulated AMR operates as an autonomous material-handling agent capable of sensing its environment, determining its position, receiving task assignments, calculating navigation paths, avoiding obstacles, transporting goods, and monitoring its battery state. The navigation process follows the workflow illustrated in Fig. 3 of the manuscript: sensor acquisition is followed by localization and mapping, global/local path planning, obstacle detection, and navigation control.

Global route planning employs the A***** algorithm, while dynamic path adjustment is used when obstacles or changing traffic conditions affect the initially selected path. Multi-agent coordination is applied to manage simultaneous AMR movements, particularly at intersections and congested aisle segments. In Table 5, the existing energy model reports an average battery capacity of 3.5 kWh, a charging time of 1.8 h, an average robot energy consumption of 2.4 kWh/day, and an average robot utilization of 82%.

Table 5 AMR operational and energy parameters

Parameter	Value/Method	Role in Simulation
Sensor configuration	LiDAR + camera + IMU	Perception/localization
Localization	SLAM	Position estimation
Global path planning	A*	Initial shortest feasible path
Local routing	Dynamic adjustment	Obstacle/congestion response
Coordination	Multi-agent	Collision and traffic control
Battery capacity	3.5 kWh	Available onboard energy
Charging time	1.8 h	Charging-cycle duration
Average energy consumption	2.4 kWh/day	Reported energy performance
Average utilization	82%	Reported fleet utilization
Average travel distance	6.1 km/day	Reported robot movement
Processing rate	9.6 orders/h/robot	Reported robot productivity

4.3 Reinforcement-learning experimental configuration

The reinforcement-learning mechanism was employed for dynamic task allocation. At each decision epoch, the controller evaluated the current warehouse state and selected an AMR-task assignment. The experimental reinforcement-learning state is explicitly formulated as follows:

$$z_t = \varnothing\left(s_t\right) \tag{8}$$

where z_t is the numerical state vector provided to the RL model, s_t is the warehouse state defined in Eq. (6), $\varnothing(\cdot)$ is the state-encoding function, t is decision time. Eq. (8) expresses the conversion of the warehouse's operational state into a numerical representation suitable for reinforcement-learning computation. The encoding function may involve normalization, categorical encoding, and a fixed-size representation of robot and task information, depending on the actual implementation.

The action corresponds to assigning an available AMR to an eligible warehouse task. A suitable reward formulation consistent with the paper's optimization objectives is:

$$r_t^{exp} = -\left[\beta_1 T_t + \beta_2 D_t + \beta_3 E_t + \beta_4 C_t + \beta_5 W_t \right] \tag{9}$$

where r_t^{exp} refers to reward calculated in the experimental configuration, $T_t^{\cdot}$ is task completion-time metric, as defined in Eq. (7), $\hat{D}_t$ is total AMR travel distance, $\hat{E}_t$ is total AMR energy consumption, $\hat{C}_t$ is congestion penalty, $\hat{W}_t$ is queueing delay during the decision interval, β_k is nonnegative experimental reward weight (k = 1, . . ., 5). Eq. (9) represents a possible experimental reward specification incorporating queueing delay explicitly. It is consistent with the manuscript's stated intention to reduce travel, energy consumption, congestion, and operational delays.

4.4 Experimental procedure

Each simulation experiment is organized into initialization, order generation, task allocation, path planning, task execution, energy management, and performance-recording stages. At initialization, the warehouse state, inventory locations, robot positions, battery conditions, and order queues are established. Customer orders are then transferred from the WMS to the FMS, where the task-allocation mechanism selects suitable AMRs.

After assignment, the navigation module generates a route between the robot's current position, the designated storage location, and the destination station. During movement, multi-agent coordination continuously monitors traffic interactions. When a planned route becomes obstructed or congested, dynamic route adjustment generates an alternative feasible path. Robot battery states are simultaneously monitored, and robots approaching the specified energy threshold are scheduled for charging subject to operational demand and charging availability.

The simulation records task completion time, travel distance, throughput, utilization, energy consumption, picking performance, and operational cost. The four experimental scenarios used for comparative evaluation are summarized in Table 6.

Table 6 Experimental scenarios for comparative evaluation

Scenario	Task allocation	Routing	Multi-Agent coordination	Energy-aware scheduling	Purpose
S0: Manual baseline	Manual	Human determined	No	No	Existing reference baseline
S1: Conventional AMR	Conventional/FIFO or nearest-task*	Static A*	Basic	No	AMR baseline
S2: Optimized routing AMR	Conventional*	Dynamic A*	Yes	No	Routing contribution
S3: Proposed framework	RL-based	Dynamic A*	Yes	Yes	Full integrated framework

*Use only the conventional allocation rule actually implemented in the additional experiments.

4.5 Repeated runs and statistical analysis

Performance metric, the mean and standard deviation were calculated across the independent runs:

$$\bar{y} = \frac{1}{K}\sum_{k=1}^{K} y_k, \quad S_y = \sqrt{\frac{\sum_{k=1}^{K}(y_k - \bar{y})^2}{K-1}} \tag{10}$$

where $\bar{y}$ is the sample mean of the evaluated performance metric, y_k is the observed metric value in simulation run k, K is the total number of independent simulation runs, $K \geq 2$, k is the simulation-run index, S_y is sample standard deviation. Eq. (10) calculates the average and sample standard deviation of a performance metric across independent simulation runs. It can be applied separately to fulfillment time, throughput, travel distance, energy consumption, and operational cost. Where appropriate, 95% confidence intervals were calculated to quantify the variability of the estimated performance. The same workload conditions were applied to competing methods within each experimental replication to ensure a consistent comparison. The performance metrics used for evaluation are shown in Table 7.

Table 7 Performance metrics used for evaluation

Metric	Definition	Unit	Desired direction
Order fulfillment time	Order arrival to completion	min/order	↓
Warehouse throughput	Completed orders per hour	orders/h	↑
Travel distance	Distance traveled during operation	km/day	↓
Picking accuracy	Correctly processed items/orders	%	↑
Robot utilization	Active operating time / available time	%	↑
Idle time	Nonproductive available time	%	↓
Energy consumption	Energy consumed per robot	kWh/day	↓
Operational cost	Modeled cost per completed order	USD/order	↓
Queueing delay	Waiting before task execution	min	↓

4.6 Ablation study

In Table 8, an ablation experiment is designed to investigate the individual contribution of the major optimization mechanisms. Starting from the complete proposed framework, one optimization component is disabled at a time while the remaining warehouse configuration and workload conditions are maintained. This design allows changes in fulfillment time, throughput, travel distance, congestion, utilization, and energy consumption to be associated more directly with individual system components.

Table 8 Proposed ablation experimental design

Configuration	RL task allocation	Dynamic routing	Multi-agent coordination	Energy scheduling
Full proposed system	✓	✓	✓	✓
A1: Without RL	–	✓	✓	✓
A2: Without dynamic routing	✓	–	✓	✓
A3: Without coordination	✓	✓	–	✓
A4: Without energy scheduling	✓	✓	✓	–

During each simulation run, customer orders are generated and transferred from the WMS to the fleet management layer for robot assignment. Dynamic task allocation was performed using the proposed reinforcement-learning mechanism, while A*-based and dynamic path-planning algorithms determine efficient routes between storage, picking, and shipping locations. Multi-agent coordination is employed for traffic management, collision avoidance, and congestion reduction [11]. The battery status of robots is constantly tracked so as to enable energy-aware scheduling algorithms to select suitable charging times for robots in order to avoid disrupting warehouse activities. Such systems resemble the navigation system, fleet management, path planning, WMS, analytics, cloud computing, and energy management systems of the proposed architecture [12].

In terms of comparative analysis, the proposed AMR-based warehouse system design is compared to the traditional manual warehouse design. The key performance metrics include average order fulfillment time, warehouse throughput, travel distance, picking efficiency, operational cost, robot utilization rate, and energy consumption. As established in the experimental setup, the robot utilization rate is 82%, the average travel distance was 6.1 km/day, the average energy consumption rate was 2.4 kWh/day, and the processing rate was 9.6 orders/hour per robot.

The experimental comparison is designed to determine whether intelligent task allocation and optimized routing can improve warehouse productivity while reducing unnecessary movement and resource consumption. The baseline manual warehouse achieves approximately 320 orders/hour, whereas the AMR-enabled configuration achieves approximately 470 orders/hour. Average order-fulfillment time decreased from 18.4 min to 11.2 min, and operational cost decrease from $3.20 to $2.10 per order. These measurements provide the quantitative basis for evaluating the effectiveness of the proposed AMR-based logistics optimization framework [13-14].

5. Results

As illustrated through simulation experiments, the newly introduced AMR optimization framework leads to a marked improvement in the performance of warehouse logistics. Table 9 presents the performance comparison between the manual warehouse system and the proposed AMR-based warehouse system. As seen from the results, notable gains arise in the performance of warehouse logistics due to the use of AMRs. For example, one of the most important achievements made is an estimated 39% improvement in order fulfillment times, primarily driven by automated item delivery and efficient robot movement algorithms.

Another improvement is a noted increase of nearly 47% in warehouse throughput. In addition, the reduction in workers' travel distance by more than 67% makes it clear that the introduction of AMRs creates a win-win situation regarding ergonomics. Instead of manually transporting items across large warehouses, workers can concentrate on value-added activities such as quality control and order monitoring. Also, picking accuracy increases to as much as 98.5%. These achievements clearly show that AMRs offer great advantages to smart warehouses in modern-day Industry 4.0.

Table 9 Performance comparison between manual and AMR systems

Performance metric	Manual warehouse system	AMR-based warehouse system	Improvement (%)	Explanation
Average order fulfillment time	18.4 minutes	11.2 minutes	39.1%	AMRs reduce travel time through optimized path planning and automated transport
Warehouse throughput	320 orders/hour	470 orders/hour	46.9%	Parallel robot operations increase order processing capacity
Worker travel distance	9.8 km/day	3.2 km/day	67.3%	Robots transport goods, reducing worker walking distance
Picking accuracy	94%	98.5%	4.8%	Automated item delivery improves order accuracy
Labor utilization	High manual labor	Reduced manual labor	—	Workers focus on supervision and packing rather than transportation
Operational cost (per order)	$3.20	$2.10	34.4%	Automation reduces labor and operational inefficiencies
System scalability	Limited	Highly scalable	—	Additional robots can be integrated into the system easily

Fig. 4 demonstrates how the increase in warehouse throughput is attained using the AMR systems. Throughput refers to the rate of order completion per hour and serves as a key performance parameter for measuring operational efficiency in logistics. In the experimental analysis, the throughput is determined in several operating periods. The manual warehouse system completes approximately 320 orders per hour; however, its performance is limited by long travel distances and manual handling bottlenecks. On the other hand, the AMR-enabled warehouse system achieves an average throughput of approximately 470 orders per hour, representing an increase of nearly 47%.

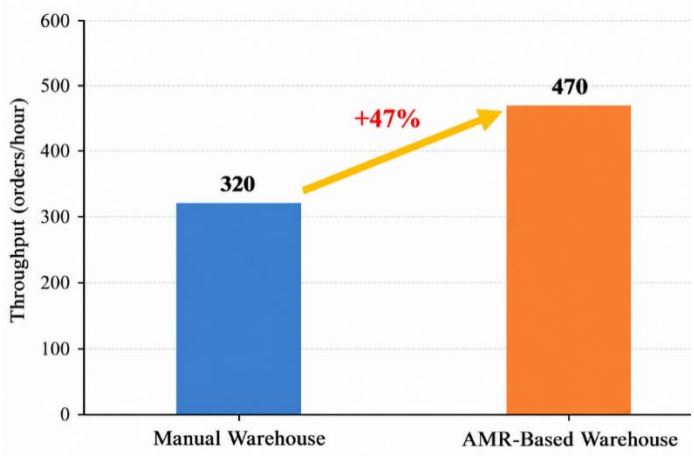


Fig. 4 Warehouse throughput improvement using AMR systems

Fig. 5 depicts the effect of optimized path planning on decreasing the travel distance covered by robots in AMR systems for warehouses. Travel distance is a vital metric in the logistics industry since it influences the total time taken to fulfill orders, energy usage, and the efficiency of the system. In regular routing mechanisms, robots are subjected to a pre-planned route, which may not be optimal and could cause wastage of resources, time inefficiency due to taking detours, and inefficiencies in traffic management in narrow aisles within warehouses. The proposed optimal system includes the deployment of routing algorithms like the A* algorithm and dynamic routing algorithms where routing pathways change dynamically depending on the status in the warehouse. The simulation result reveals that optimal path planning reduces travel distance by 32%. It is also worth noting that AMR is flexible in the management of its operations. AMR can be seamlessly included in fleets without interfering with existing processes, which makes the warehouse more adaptable to varying demand seasons [15].

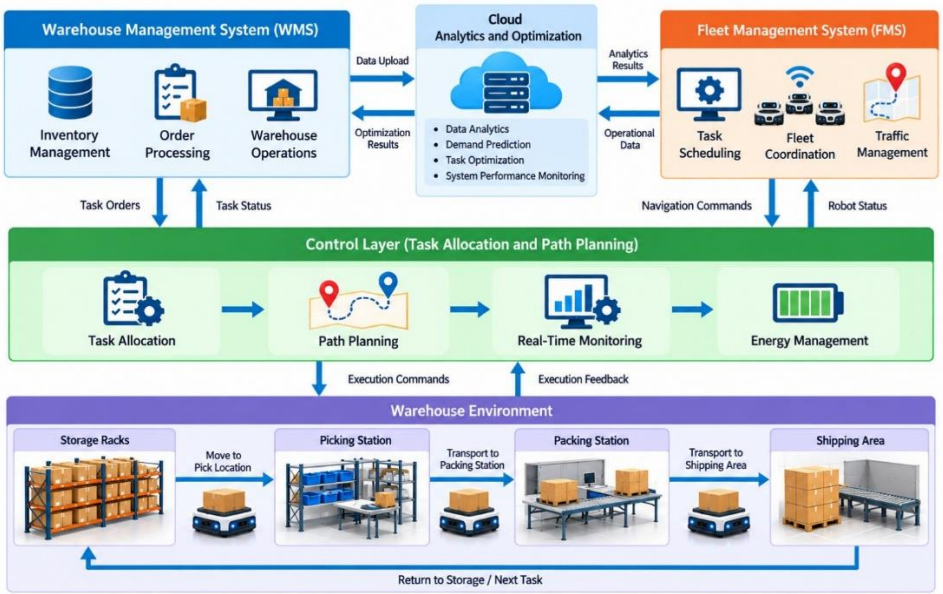


Fig. 5 Reduction in robot travel distance using optimized routing

Table 10 illustrates the energy consumption behaviors and operational efficiency of the AMR fleet operating in the smart warehouse environment. The efficient use of energy is considered to be a key issue in a logistics system of this scale due to the direct influence of energy consumption on the cost and sustainability of operations. Within the investigated simulation, average modeled energy consumption was 2.4 kWh per robot per operating day. This value should be interpreted as a simulation parameter/result under the specified robot duty cycle, routing conditions, battery model, and charging strategy rather than as a universal energy benchmark for commercial AMRs. Direct energy-efficiency comparison with alternative industrial automation systems requires equivalent payload, operating duration, travel distance, and duty-cycle conditions.

Under the investigated simulation conditions, the integrated AMR configuration achieves a 39.1% reduction in average order-fulfillment time and a 46.9% increase in warehouse throughput relative to the modeled manual baseline. These improvements are primarily associated with parallel robot execution, reduced material-transport walking, dynamic task assignment, and shorter routing paths. Nevertheless, the comparison demonstrates performance relative to the specified simulation baseline and should not be interpreted as evidence that equivalent improvements will necessarily occur in every physical warehouse.

Table 10 Energy consumption and operational efficiency of AMR fleet

Metric	Measured value	Unit	Operational impact
Average energy consumption per robot	2.4	kWh/day	Indicates daily energy usage for a typical AMR operating in warehouse logistics tasks
Average robot travel distance	6.1	km/day	Reduced travel distance due to optimized routing algorithms
Battery capacity	3.5	kWh	Typical lithium-ion battery capacity for warehouse AMRs
Battery charging time	1.8	hours	Time required to recharge robot battery at charging stations
Average robot utilization rate	82	%	Percentage of operational time robots actively perform logistics tasks
Idle time	18	%	Time robots remain inactive due to task scheduling or charging cycles
Fleet operational efficiency	35	% improvement	Overall system efficiency increase compared to manual warehouse operations
Average orders processed per robot	9.6	orders/hour	Individual robot productivity within the warehouse system

5.1 Challenges and limitations

The findings should be interpreted within several limitations. First, the evaluation is simulation-based and does not fully reproduce sensing noise, wheel slip, localization drift, communication latency, packet loss, or unexpected human behavior encountered in physical warehouses. Second, robot failures and sensor anomalies are not comprehensively modeled. Third, battery degradation and charging-station congestion may influence long-term fleet availability but are simplified in the present framework. Fourth, scalability may introduce nonlinear congestion and computational complexity as fleet size and warehouse density increase. Fifth, the reported performance is dependent on the investigated warehouse layout, order-arrival pattern, AMR configuration, and simulation assumptions. Consequently, physical AMR experiments, larger-scale fleet evaluation, communication disturbance testing, sensor-fault analysis, and digital-twin validation constitute important directions for future research.

6. Conclusions

This study developed and evaluated an integrated AMR-based framework for smart warehouse logistics optimization. The proposed framework combines autonomous sensing and navigation, WMS integration, fleet management, reinforcement-learning-based task allocation, dynamic path planning, multi-agent coordination, and energy-aware scheduling. A simulated warehouse containing 1,000 storage locations and 50 AMRs was used to evaluate the proposed framework against conventional manual warehouse operations.

The AMR-based system reduced average order fulfillment time from 18.4 min to 11.2 min, corresponding to a reduction of approximately 39.1%. Warehouse throughput increased from approximately 320 to 470 orders/hour, representing an increase of approximately 46.9%. Worker travel distance decreased from 9.8 to 3.2 km/day, corresponding to a reduction of approximately 67.3%, indicating the potential of AMRs to reduce repetitive material-transport activities. Picking accuracy

increased from 94% to 98.5%, while operational cost decreased from USD 3.20 to USD 2.10 per order. The AMR fleet achieved an average robot utilization rate of 82%, demonstrating that coordinated task allocation and routing can support efficient utilization of robotic resources.

Overall, the findings indicate that integrating intelligent task allocation, autonomous navigation, and warehouse information systems can substantially improve logistics efficiency and operational flexibility. Nevertheless, the present results are simulation-based and should therefore be validated using physical AMRs and real warehouse operational data. Future research will investigate digital-twin-based warehouse simulation, large-scale multi-robot coordination, human–robot safety, communication latency, and adaptive energy-aware scheduling under dynamically changing warehouse demand.

Conflicts of Interest

The authors declare no conflict of interest.

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