

AI-enhanced Digital Twin systems for warehouse logistics optimization: A review of challenges with solutions and future directions

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ABSTRACT

Digital transformation is revolutionizing warehousing by integrating advanced technologies like Digital Twins, AI, and IoT. Digital Twins create virtual warehouse replicas for simulation and optimization, enhancing resource allocation and proactive problem-solving. AI-driven systems predict and optimize processes, while Automated Guided Vehicles (AGVs) streamline the movement of goods. IoT improves connectivity and data collection, supporting decision-making through machine learning and deep learning. Robots, utilizing reinforcement learning and computer vision, automate tasks like picking and packing, boosting efficiency and reducing errors. Additionally, anomaly and intrusion detection enhance security. This review highlights key advancements in path planning, task allocation, inventory management, and storage assignment, which improve operational effectiveness. It also addresses the lack of analysis on the economic impacts of digital transformation, particularly in cost reduction, return on investment (ROI), and customer satisfaction. The paper identifies research gaps, including the integration of sustainability, adaptation to dynamic environments, collaborative robots, and optimization of reverse logistics. This review provides a foundation for future research on the potential of digitalization to transform warehousing practices.

1. Introduction

The digital transformation of warehouse logistics is fundamentally reshaping the way goods are managed, stored, and distributed. As the logistics industry faces increasing demands for efficiency, speed, and flexibility, technologies such as Digital Twin (DT), Artificial Intelligence (AI), and the Internet of Things (IoT) are emerging as key enablers of this transformation [1,2]. DT technology creates high-fidelity virtual replicas of physical systems, enabling real-time simulations, monitoring, and optimization [3,4]. These virtual models allow warehouse operators to predict potential issues, test new strategies without disrupting ongoing operations, and make data-driven decisions to enhance performance.

In modern warehouses, the integration of AI with DT systems is particularly valuable. AI algorithms, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), augment the capabilities of DT by analyzing large volumes of real-time data, providing predictive insights, and automating complex tasks [5–7]. For instance, AGVs and robots, powered by AI, can autonomously navigate and perform tasks such as picking, packing, and sorting [8]. These systems not only increase operational efficiency but also reduce human error, enhance throughput, and enable more flexible and scalable

warehouse operations. Alongside automation, IoT devices play a crucial role in enabling these technologies by providing real-time data and connectivity [9]. With sensors, RFID tags, and smart devices embedded throughout the warehouse, IoT systems continuously collect data on inventory levels, warehouse conditions, and equipment performance. This information is fed into DT models, allowing for dynamic adjustments to operations, such as optimizing storage layouts, adjusting inventory levels, and fine-tuning supply chain operations [10,11]. As a result, warehouses can operate more efficiently, respond to changing demands faster, and make better-informed decisions.

The invention of DT technology marked the beginning of a new era in warehouse logistics, evolving through several distinct phases as illustrated in Fig. 1. Initially, during the DT Conceptualization (2002–2010) phase, DTs were introduced as static digital models primarily designed for system visualization and basic monitoring. With the rise of Industry 4.0 and the Industrial Internet of Things (IIoT) (2011–2015), these models advanced into interactive, data-driven systems capable of real-time data collection and communication between physical and digital environments. The AI Augmentation phase (2015–2019) brought the integration of ML and DL, enabling predictive analytics and process optimization in warehouse operations. The next stage,

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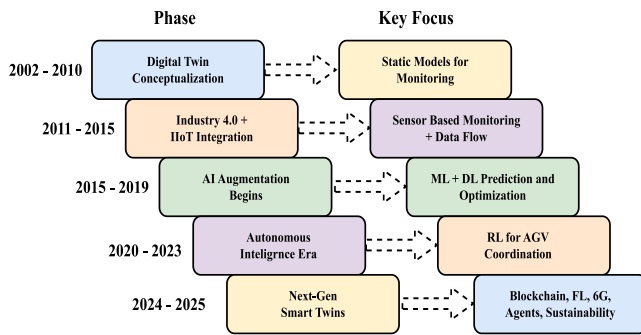


Fig. 1. Evolution of digital twin technologies for warehouse logistics (2002–2025).

the Autonomous Intelligence Era (2020–2023), witnessed the adoption of RL and intelligent robotics, allowing AGVs and multi-robot systems to perform autonomous decision-making and adaptive coordination. Finally, the Next-Generation Smart Twins (2024–2025) phase represents the emergence of distributed, intelligent ecosystems that integrate blockchain, federated learning (FL), and 6G technologies for enhanced sustainability, scalability, and secure real-time collaboration. Collectively, the diagram captures this historical trajectory from basic monitoring systems to intelligent, interconnected, and self-optimizing warehouse ecosystems [12,13].

However, modern warehouses continue to face several operational challenges that hinder their performance. Key challenges include inefficient path planning, poor resource allocation, and difficulties in inventory management due to the lack of predictive capabilities [14]. Path planning for AGVs can lead to delays and increased travel times, while improper resource allocation results in underutilized warehouse space and equipment [15]. Traditional systems, which rely on static data and manual decision-making, struggle to meet the fast-paced demands of today's logistics environments. Moreover, inventory management remains a critical challenge, with stockouts and overstocking often resulting from outdated forecasting methods. These challenges highlight the need for more adaptive, real-time solutions capable of responding dynamically to warehouse operations and increasing demands [16].

In response to these challenges, the integration of AI-driven DT technologies offers a transformative solution [17–19]. By leveraging AI algorithms such as RL and ML, these technologies enable real-time optimization of warehouse systems, allowing for dynamic task scheduling, efficient AGV path planning, and more accurate inventory forecasting. The use of reinforcement learning ensures that AGVs can continually adapt their routes to minimize travel time and energy consumption, while ML helps predict demand fluctuations and optimize stock levels, reducing the risk of overstocking or stock-outs. These capabilities improve the efficiency of warehouse operations, reduce costs, and enhance scalability.

Moreover, the integration of IoT devices plays a critical role in this transformation. IoT provides continuous streams of data from sensors, RFID tags, and other connected equipment, which is fed into the DT model [20–22]. This data stream enables real-time monitoring of warehouse conditions, equipment status, and inventory levels, allowing for proactive adjustments to operations. By combining the AI-powered DT with IoT, warehouses can operate with greater flexibility, reduce downtime, and respond quickly to changes in demand or supply chain disruptions [23–26].

Despite the significant advantages of AI and DT integration, several research gaps [27]. The economic implications of implementing these technologies, particularly in terms of Return on Investment (ROI) and long-term financial sustainability, have not been thoroughly explored. The high costs of implementing high-precision localization systems, AGV fleet management, and AI training models are substantial, yet

their impact on operational efficiency and cost reduction remains under-quantified. Additionally, the environmental impact of AI-driven DT systems, especially regarding energy consumption and carbon footprint, has not been adequately addressed. Optimizing energy-efficient routing, adaptive task scheduling, and eco-friendly warehouse designs should be prioritized to mitigate these challenges.

The future of warehouse logistics lies not only in improving operational efficiency but also in addressing emerging challenges such as reverse logistics, dynamic environment adaptation, and the integration of collaborative robots. With the growth of e-commerce and the shift towards just-in-time manufacturing, the demand for real-time, adaptive warehouse systems that can quickly respond to changing conditions is rising. AI-powered DT are poised to address these challenges, offering solutions for multi-objective scheduling, inventory management, space optimization, and real-time adaptive decision-making.

This paper provides a comprehensive review of the integration of AI and DT technologies in warehouse logistics [28]. We examine how these technologies are being applied in key areas such as path planning, task allocation, and inventory management. Additionally, we discuss emerging technologies such as FL, blockchain, and 6G networks, which offer new opportunities to enhance the scalability, security, and connectivity of warehouse operations. Finally, we identify critical research gaps and outline potential directions for future studies, focusing on the integration of sustainability, adaptive strategies, and collaborative robotics into digital warehouse systems.

The integration of AI-driven DT is transforming warehouse logistics by providing real-time insights, predictive capabilities, and autonomous optimization [29–31]. These technologies enable warehouses to meet the increasing demands of modern supply chains. However, to fully realize their potential, further research is needed to address the economic, environmental, and operational challenges. This paper aims to provide a foundation for future research and development in this field, offering valuable insights into the evolving role of AI-driven Digital Twins in the logistics industry [32,33]. (see Fig. 2).

The main contributions of this article are as follows:

- We provide a thorough analysis of the Digital Twin-based warehouse logistics optimization approach.
- We present a comprehensive study of the key operational challenges faced by warehouses in the digital era. Despite the advances in automation and digitization, several critical problems remain within warehousing operations. These include inefficiencies in task allocation, suboptimal path planning, poor space utilization, delays in inventory management, and challenges in coordinating autonomous systems such as robots and AGVs.
- We explore the tools and technologies used for constructing highly efficient Digital Twin simulations and the potential technologies, such as computer vision, reinforcement learning, and other AI techniques, that can resolve the existing problems in digital warehousing. Specifically, we will focus on how these advanced technologies can be integrated with digital twin systems to improve the overall optimization of warehouse logistics.

The remainder of this paper is organized as follows: Section 2 presents a literature review on challenges in warehouse operations, examining the operational difficulties encountered in modern warehouse environments. Section 3 explores solutions for warehouse challenges, detailing how AI methodologies integrated with digital twin technology address key logistics optimization problems. Section 5 discusses research gaps and future directions, identifying unexplored areas and emerging opportunities in the field. Finally, Section 6 concludes the paper by summarizing the key findings.

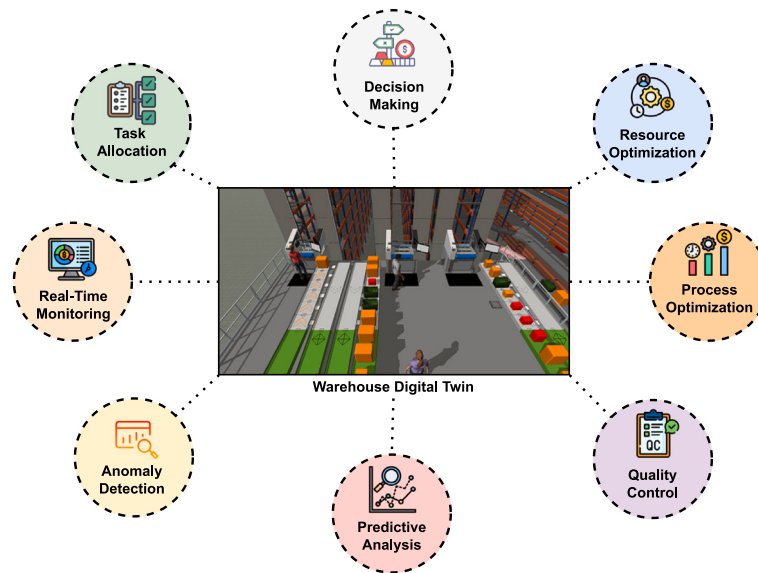


Fig. 2. Applications of Digital Twin in warehouse logistics.

2. Literature review on challenges in warehouse operations

Driven by rapid advancements in digital twin technology and its application across various sectors, recent reviews have emerged to investigate its transformative impact and new trends. For example, one study [34] examines the DT concept in the context of Industry 4.0, underscoring its integration with key enabling technologies such as artificial intelligence (AI) and the Industrial Internet of Things (IIoT), while also highlighting the fast-paced evolution of DT applications in manufacturing. In another review [35], the authors discuss evolving definitions and fundamental attributes of DT technology, detailing its multidisciplinary applications and providing design insights related to socio-technical factors and the complete DT lifecycle [36].

Other investigations [37,38] have delved into the influence of DT within IIoT ecosystems. One such work [35] presents an extensive overview of DT definitions and features, exploring its expanded role in IIoT environments through various application scenarios, software architectures, and prospective evolution paths as part of the broader process of softwarization. A separate study [39] focuses on DT technology within IIoT frameworks by examining enabling technologies like AI and blockchain; it discusses real-world implementations, architectural models, and advanced software tools for high-fidelity DT modeling in secure and intelligent IIoT systems.

Security aspects have also received significant attention in the literature. One paper [40] reviews security and privacy challenges in generic DT systems and discusses potential defense mechanisms, while another study [41] investigates the security landscape of DT technology within the Industry 4.0 paradigm. The latter work analyzes potential threats across different DT functionality layers and proposes initial recommendations for enhancing security and trustworthiness in industrial DT deployments.

Additionally, DT integration in wireless networks has been explored [42,43], providing a taxonomy of key DT concepts for wireless systems, discussing design considerations, deployment trends, and security issues, as well as examining air interface challenges. Similarly, a review [37] assesses the role of DT technology in smart industries from the perspectives of communications and computing, considering trends in next-generation wireless technologies such as 5G and beyond, along with edge and cloud computing paradigms [36,44]. Furthermore, another survey [45] investigates DT deployment in 6G communication systems, critically evaluating potential use cases and applications [46].

Finally, the broader adoption and development of DT in industrial settings are discussed in additional reviews. One study [47] offers an

overview of DT applications in various industrial domains, including product design, production processes, and health management, while another paper [48] focuses on DT applications specifically in the construction industry, emphasizing its role in lifecycle management. This body of work collectively provides a robust foundation for understanding the multifaceted evolution, applications, and challenges of digital twin technology across industries.

2.1. Operational challenges

With the increasing demand for precise and fast order fulfillment, warehouses are leveraging cutting-edge technologies to streamline their internal operations and enhance their efficiencies. Path planning is essential for ensuring the seamless movement of goods within the warehouse while minimizing travel time and maximizing productivity. The challenge lies in devising optimal routes for AGVs, automated storage and retrieval systems (AS/RS), robots, human operators, etc., to navigate along the complex layout of storage racks and workstations within the warehouse. Fig. 3 presents an overview of the main challenges encountered in warehouse logistics, highlighting task allocation, path planning, localization, and object detection as the most frequently discussed areas in recent literature. As discussed by Zhang et al. [49], an improved Q-learning algorithm to optimize multi-AGV route planning in large-scale warehouse environments was proposed. The algorithm considers AGV load status, minimizes turns, and enables real-time collision avoidance. The algorithm's effectiveness is demonstrated through three case studies. In case 1, differentiating between loaded and unloaded AGVs resulted in a 10-second reduction in travel time and an 11.11% improvement in efficiency. Case 2 showcased real-time collision avoidance for new 145814 AGVs entering a system, significantly reducing task completion time and route computation time while increasing throughput. Case 3 optimized routes for multiple loaded and unloaded AGVs simultaneously, minimizing energy consumption and avoiding collisions. Similarly, Tang et al. [50] developed a digital twin framework for demand forecasting and inventory management in small-scale cyclical industries, such as textiles. This framework utilizes a roulette genetic algorithm for demand prediction and aims to optimize inventory levels in line with predicted demand, thereby mitigating risks associated with economic downturns and seasonal fluctuations. A case study of a small-scale textile company demonstrated the framework's effectiveness in generating accurate demand forecasts and optimizing inventory levels, highlighting the importance

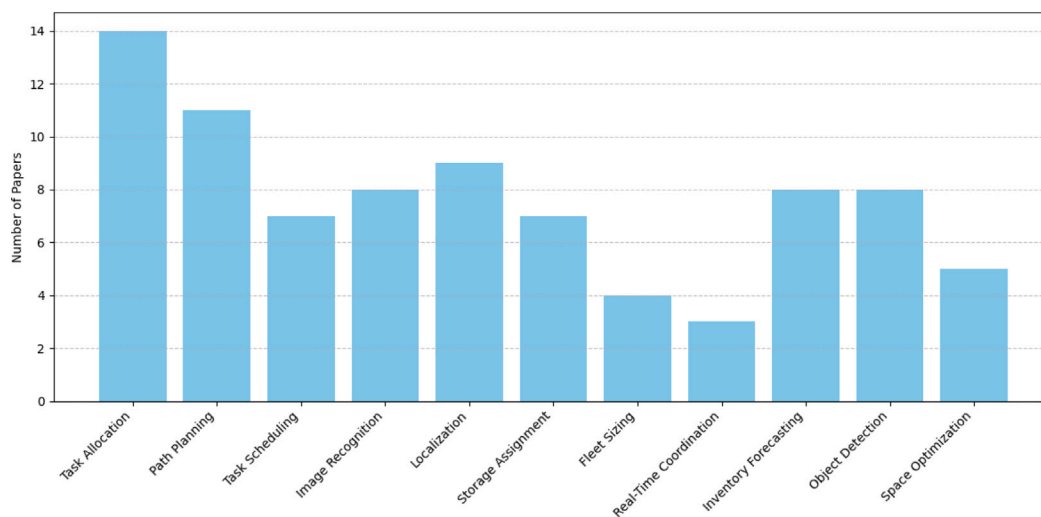


Fig. 3. Overview of discussed challenges in warehouse logistics literature.

of integrating demand forecasting with inventory management in smart warehouses for cyclical industries.

In the area of intelligent warehousing, there is a growing reliance on multi-robot systems that assist in minimizing costs and improving operational efficiency [51]. In fact, the complexity inherent in warehouses, coupled with the use of advanced technology and the need for swift order fulfillment to meet customer demands, necessitates solutions beyond the capabilities of single robots. Thus, deploying robots in warehouses has become crucial for boosting efficiency. Task allocation/assignment is concerned with deliberately distributing tasks and responsibilities among a multi-robot system to ensure optimal performance and competent utilization of resources. In intelligent warehouses, a crucial role is played by using a fleet of mobile and automated picking robots, which are tasked with efficiently processing orders by fetching items from the shelves and dropping them in the delivery stations. Zhao et al. [52] focused on the scheduling and navigation of multiple mobile robots by highlighting the inefficiency in traditional methods where robots were assigned tasks without considering the overall transportation time, leading to uneven task distribution and longer execution times. The authors presented a case study using a hierarchical Genetic Algorithm-Ant Colony Optimization (GA-ACO) algorithm to optimize task assignments and minimize total transportation time. This approach was tested in a simulated warehouse environment with obstacles, where two robots successfully completed 20 tasks, demonstrating the effectiveness of the proposed method in reducing overall transportation time and improving operational efficiency. Moreover, Agrawal et al. [53] proposed RTAW, a reinforcement learning-based algorithm for multi-robot task allocation in warehouse environments. This algorithm is designed to enhance cooperation among robots, minimizing total travel delay and improving makespan for large task lists. Extensive experiments demonstrated RTAW's superiority over traditional methods, with up to 14% improvement in total travel delay. The results highlight RTAW's adaptability to various warehouse layouts and its potential for real-world applications in automating fulfillment and distribution centers. Among the reviewed literature, 14 papers specifically shed light on task allocation problems, with recent works highlighting the potential of machine learning technologies in optimizing warehouse operations. Table 1 provides an extensive overview of the existing approaches and their contribution to warehouse logistics optimization. (see Fig. 4).

The localization problem is accurately estimating the current position of the system. Tripicchio et al. [82] and Yang et al. [80] addressed the challenges in warehouse logistics and proposed solutions using RFID technology by focusing on optimizing warehouse location assignment using RFID for real-time information capture and an improved

particle swarm optimization algorithm, as well as introducing four least mean squares methods for estimating the 3D positions of passive UHF RFID tags, emphasizing the importance of precise localization for efficient robot motion and planning in the context of Industry 4.0. This highlights the potential of RFID technology and advanced algorithms to optimize warehouse operations, improve inventory control, and enhance process efficiency in industries like logistics and supply chain management. Moreover, Haibin et al. [83] focused on optimizing automated warehouse location in intelligent manufacturing. It emphasizes the importance of location allocation and optimization in warehouse management, introducing a multi-objective genetic algorithm to improve efficiency and shelf usage. Traditional methods are highlighted as inefficient for large-scale operations, while the genetic algorithm offers a simple yet effective solution for quick, satisfactory results in real-world scenarios. This approach ensures improved warehousing efficiency and shelf stability, crucial in the evolving landscape of intelligent manufacturing and automated warehousing.

The image information recognition problem refers to the capability of computers to determine and classify items, places, actions, and people through digital imagery. He et al. [54] studied the challenges in smart factory environments, where the diversity of goods in terms of shape and color, coupled with the need for real-time processing, necessitates advanced solutions. Traditional static vision image processing methods often fall short in addressing these complexities, leading to inefficiencies in warehouse logistics management. To overcome these limitations, this study proposes the optimization of a YOLOv3 model for enhanced warehousing housed goods recognition. Experimental results validate the effectiveness of this approach, demonstrating its potential to significantly improve the speed and accuracy of goods recognition within intelligent warehouse systems. Zhuang et al. [56] addressed the optimization of cooperative task planning for diverse multi-robot systems within order-picking warehouses. The research emphasizes the complexities arising from heterogeneous agents, interconnected utilities, and intricate intertask dependencies. To tackle these challenges, a novel mapping mechanism is introduced, reformulating the problem as open shop scheduling with sequence-dependent set-up and transportation times. The study further proposes an efficient mixed-integer linear programming model for smaller problems and a hybrid artificial bee colony algorithm for larger-scale scenarios. The efficacy of these methods is validated through simulation experiments, demonstrating their potential to enhance task planning and coordination in warehouse environments. Additionally, Bolu & Korcak [55] proposed the development of an adaptive task planning approach for multi-robot smart warehouses, focusing on optimizing the Robotic Mobile Fulfillment System (RMFS) to efficiently manage resources and tasks.

Table 1
Overview of existing problems, approaches, technologies, and contributions in warehouse logistics.

Problem	Solution approach	Technologies utilized	References	Contributions
Image Recognition Problem	Simulation	Machine Vision Technology	[54]	A study on image detection and classification of warehouse items using enhanced YOLOv3.
Task Scheduling Problem	Heuristic Methods	Robot	[55]	Robotic Mobile Fulfillment Systems for efficient resource utilization in smart warehouses.
	Mixed-Integer Linear Programming	Robot	[56]	Optimal planning for small-scale challenges with setup and transportation delays.
Task Allocation	Integer Programming	Robot	[57]	Conversion of MRTA issues into transportation problems for enhanced task processing.
	Heuristic Methods	Robot	[58–60]	New methodologies for MRTA including scheduling and navigation.
	Dynamic Programming	Robot	[61]	Real-time dynamic MRTA using adaptive task pools and CMA-ES algorithm.
Path Planning	Linear Programming	IoT, Robot, AGV, RFID	[62–65]	Spatial layout optimization in intelligent warehouses via IoT and blockchain.
	Integer Programming	Robot, AGV	[66,67]	Collision-free path planning solutions for enhanced AGV routing.
	Dynamic Programming	Robot, AGV	[68–71]	Stable and real-time path planning and AGV scheduling optimization.
	Genetic Algorithm (GA)	Digital Twin, AGV	[72–75]	AGV scheduling path planning integrated with Digital Twin technology.
	Heuristic Methods	Robot, AGV	[76–78]	Advanced path planning using intelligent warehouse management algorithms.
Localization Problem	Dynamic Programming	RFID	[79]	Real-time RFID-based flexible warehouse localization improvements.
	Meta-Heuristic Optimization	RFID	[80]	Real-time warehouse information gathering using RFID technology.
	Integer Programming/GA	Automatic Control Technology	[81]	Multi-objective evolutionary algorithm for improved site allocation methods.
	Simulation	RFID	[82]	Localization of passive RFID tags for mobile robot tasks using multilateration.

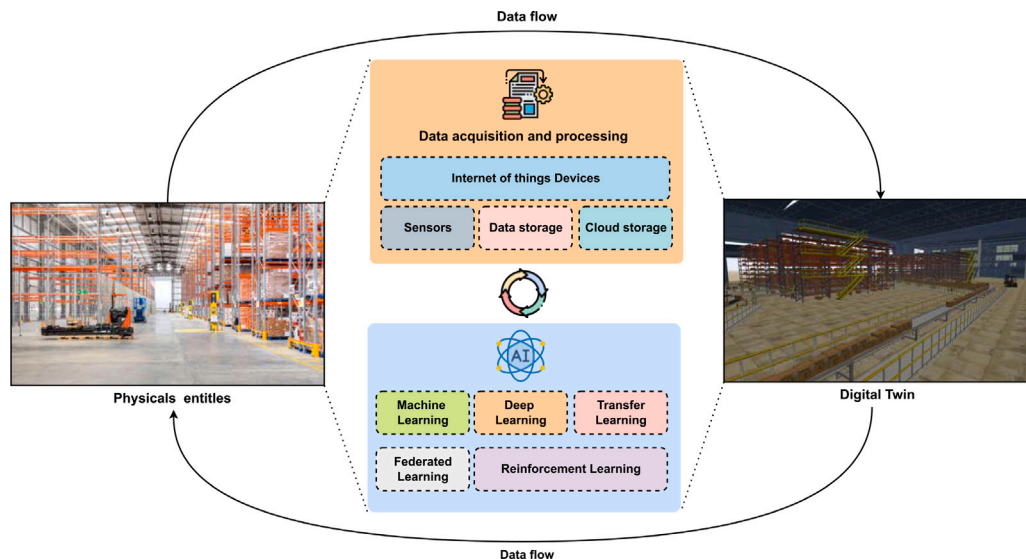


Fig. 4. Warehouse logistics optimization through Digital Twin integration and AI technologies.

The study introduces a centralized task management algorithm that adapts to system dynamics and proposes an adaptive heuristic approach for assigning tasks to robots. Extensive simulations in a tic environment show that the approach significantly reduces order completion time and balances workload among robots, even with a high number of stock-keeping units (SKUs). The paper also examines the impact of various system parameters on smart warehouse design and efficiency.

The storage assignment problem focuses on finding the optimal warehouse location for incoming goods while taking into consideration

the warehouse’s capacity. A food company that faces warehouse space constraints impacting production due to uncoordinated planning and storage assignment is addressed in a study by Zhang et al. [84]. The study presents a novel strategy integrating production with randomized storage, modeled through mixed-integer linear programming and a heuristic algorithm. Numerical experiments demonstrate the strategy’s effectiveness in reducing costs and optimizing space compared to dedicated storage policies. The company’s consideration of IoT-enabled indoor positioning systems for improved warehouse management visi-

bility prompts the development of an innovative strategy integrating production planning with randomized storage assignment. This approach, leveraging IoT capabilities, aims to optimize space utilization and reduce costs in scenarios with fluctuating demands. Rjeb et al. [85] addressed the load-sizing problem of robots through a simple mixed-integer linear programming model of transporting homogeneous loads between two storage areas in the warehouse, which takes into account the number of pickup and delivery stations in the system. The packing and storage assignment problem seeks to optimize the organization and allocation of packed goods. Leng et al. [86] approached this problem by proposing a new digital twin-driven approach to optimize packing and storage in large-scale automated high-rise warehouses. The system integrates real-time data with a cyber model, enabling periodic optimization through a joint optimization model. A case study in a tobacco warehouse validates the model's effectiveness in improving utilization and efficiency. The research fills a gap in the existing literature by focusing on the joint optimization of packing and storage management, addressing the challenges of managing large-scale warehouse operations with unpredictable demands and interactions. Finally, the production–inventory problem deals with resource shortages and cost inaccuracies, which are addressed by Maity [87] through case studies illustrating real-world applications, such as a two-warehouse production–inventory model with fuzzy budget and space constraints, solved using optimal control theory to manage defective items and space scarcity. Within the same work, another case study presents a three-layer supply chain model under conditionally permissible delay in payments, formulated in fuzzy-rough and Liu uncertain environments, addressing supplier–manufacturer–retailer dynamics and incorporating factors like ideal costs and delay in payments. These examples showcase the effectiveness of intelligent techniques in optimizing warehouse performance amidst practical challenges like defective products, space limitations, and supply chain coordination.

2.2. Comparative analysis of approaches

The analysis of recent research on intelligent warehouse systems reveals clear trends, trade-offs, and emerging gaps across AGV scheduling, RFID-enabled tracking, and flexible warehousing approaches. A major trend is the shift toward fully autonomous and data-driven warehouses, integrating automated guided vehicles (AGVs), mobile robots, and sensor-based technologies under the Industry 4.0 paradigm. These systems aim to optimize task allocation, reduce human intervention, and improve operational efficiency. The adoption of RFID and IoT-enabled technologies further enables real-time monitoring of both inventory items and movable storage equipment, supporting dynamic adjustments in storage locations and capacities, as exemplified in flexible and fluid warehousing models.

A particularly notable trend is the increasing use of AI-based methods, including deep reinforcement learning (DRL), for multi-agent task allocation. Li et al. [89] introduced a DRL framework for efficient task assignment among heterogeneous AGVs, modeling the problem as a capacitated multiagent open pickup and delivery problem (CMOPDP). By incorporating heterogeneous attention, dual decoders, and entropy rewards, their approach achieves improved solution quality ($\geq 1.76\%$ over benchmarks), real-time task allocation, and robust generalization across diverse warehouse layouts. This demonstrates the growing maturity of AI-driven task allocation methods compared to traditional heuristics, offering adaptive, constraint-aware, and cooperative decision-making capabilities.

The comparative evaluation of different approaches highlights several trade-offs. High flexibility and adaptability, such as free pick-and-drop mechanisms or DRL-based task allocation, reduce lead times and operational costs but increase system complexity and training requirements. High-accuracy localization techniques, particularly RFID-based 3D multilateration with phase unwrapping, significantly improve item tracking and robot navigation but demand precise motion control,

careful calibration, and sophisticated hardware. AGV scheduling algorithms, including heuristic, hybrid, metaheuristic, and DRL-based methods, optimize throughput, energy usage, and travel time, yet they may struggle with scalability, congestion, and real-time responsiveness in large, dynamic warehouses. Specifically, DRL-based approaches offer fast inference at runtime but require substantial offline training and careful hyperparameter tuning.

The tables presented across the reviewed studies indicate the maturity and limitations of these technologies. AGV scheduling is relatively mature, performing robustly in small- to medium-scale systems but exhibiting limited scalability for high-density fleets. DRL-based task allocation, as shown by Li et al. provides high-quality adaptive solutions under complex constraints but faces challenges in training time, convergence in dense environments, and handling multiobjective optimization. RFID-based 3D localization achieves excellent accuracy in experimental setups (mean 2D error 0.21 cm; 3D error 13 cm) but remains largely untested in large-scale real-world warehouses. Flexible RFID-enabled warehousing is emerging, demonstrating potential for efficiency gains and reduced operational errors, yet relies heavily on continuous real-time monitoring and a supportive IoT infrastructure.

Several research gaps remain. Current systems rarely integrate task scheduling, multiobjective routing, storage allocation, and precise localization into a unified framework. Scalability and robustness under real-world uncertainties, such as sensor noise, multipath effects, read errors, dynamic demand patterns, or high-density AGV fleets, require further investigation. Moreover, real-time adaptive strategies for AGV task assignment, energy management, and storage reconfiguration are underexplored. Hybrid approaches that combine DRL with heuristics or optimization-based methods may balance solution quality, inference speed, and robustness. Future research should aim to develop holistic, scalable, and resilient smart warehouse systems that combine the strengths of high-accuracy localization, flexible storage, and optimized task allocation while mitigating the associated complexity and operational costs. The reviewed studies collectively suggest that while individual components of intelligent warehousing are approaching maturity, a fully integrated and robust smart warehouse system is yet to be realized. The interplay between flexibility, accuracy, operational efficiency, and AI-driven adaptability represents both a challenge and an opportunity for future research in the field. Li et al.'s work demonstrates the potential for DRL to elevate task allocation practices, indicating that AI-based coordination methods are likely to play a central role in next-generation smart warehouses.

Table 2 summarizes the state-of-the-art and commonly used baseline methods across key problem domains in warehouse logistics (path planning, task allocation, localization, scheduling, perception, real-time coordination, inventory and storage assignment). The table maps each approach to the principal tools and system contexts (e.g., Digital Twin, AGV, RFID, IoT), the evaluation metrics employed (travel time, makespan, localization error, mAP, energy consumption, etc.), and the representative performance claims reported in the literature. By consolidating Q-learning and GA variants for path planning, DRL and hybrid GA/ACO schemes for task allocation, RFID+LMS/PSO for localization, MILP hybrids for scheduling and storage, and enhanced YOLO for vision tasks, the table provides a compact reference that both identifies suitable baselines and highlights which metrics authors typically report for each domain. We note that numerical results originate from heterogeneous experimental setups and are therefore indicative rather than directly comparable; nevertheless, the table directly addresses the reviewer's concern by cataloguing contemporary methods, their reported outcomes, and the evaluation criteria that should be used when selecting baselines for future comparative experiments.

3. Solutions for warehouse challenges

As the demand for faster, more efficient order fulfillment in warehouse operations intensifies, the logistics sector faces significant operational challenges. Traditional warehouse management systems often

Table 2
Performance comparison of state-of-the-art methods for warehouse logistics optimization.

Problem domain	Approach	Tools	Performance metrics	Reported results	References
Path Planning	Q-learning (Improved)	AGV, Digital Twin	Travel time, Efficiency, Energy consumption	11.11% efficiency improvement 10s travel time reduction Real-time collision avoidance	[88], [49]
	Genetic Algorithm (GA)	Digital Twin, AGV	Route optimization, Multi-AGV coordination	Optimized multi-AGV routing with collision avoidance	[60,72,73]
Task Allocation	DRL Framework (SOTA)	Multi-AGV, Digital Twin	Solution quality, Real-time allocation	1.76% improvement over benchmarks Superior generalization across layouts Faster inference at runtime	[89]
	RTAW (RL-based)	Multi-Robot	Travel delay, Makespan	14% reduction in total travel delay Improved task cooperation and scalability	[53]
	GA-ACO (Hybrid)	Robot, Multi-Robot System	Transportation time, Task distribution	Minimized total transportation time, improved coordination	[52]
Localization	RFID + LMS (3D Multilateration)	RFID, Robot	Position accuracy (2D/3D)	Mean 2D error: 0.21 cm Mean 3D error: 13 cm High-precision multilateration	[90], [79]
	RFID + PSO	RFID	Real-time tracking, Location assignment	Optimized warehouse location assignment with improved data accuracy	[91], [80]
Task Scheduling	MILP + ABC Hybrid	Robot, Multi-Robot	Task completion time, Workload balance	Reduced delays, Balanced workload distribution	[56]
Image Recognition	YOLOv3 (Enhanced)	Machine Vision, Deep Learning	Detection speed, Accuracy	Enhanced real-time goods recognition Increased detection speed and accuracy	[54]
Real-Time Coordination	Auction Algorithm + D* Lite	Robot, AGV	Travel time, Energy consumption	Reduced energy usage, Improved throughput	[92]
Inventory Management	Roulette GA + Digital Twin	Digital Twin	Demand forecasting accuracy, Stock optimization	Accurate demand forecasts Optimized stock levels under dynamic demand	[50]
Storage Assignment	MILP + IoT	IoT, Production Planning	Space utilization, Cost reduction	Improved space usage Reduced operational costs by IoT integration	[84]
	DT-driven Joint Optimization	Digital Twin, Automated WH	Utilization rate, Efficiency	Enhanced utilization in high-rise warehouses Integrated real-time data with cyber models	[86]
Production–Inventory	Fuzzy Optimal Control	Warehouse Management	Resource allocation, Cost accuracy	Optimized defective item management Improved resource allocation under constraints	[87]

Table 3
AI-driven enhancements in Digital Twin-based warehouse systems.

AI technique	Warehouse domain	Integration with Digital Twin	Resulting optimization and benefit
Q-learning (RL) [49]	Path Planning	DT-based real-time AGV routing simulation.	Reduced travel time, energy use, improved efficiency.
GA-ACO [52]	Task Allocation	Hierarchical robot scheduling in DT environment.	Shorter completion time, enhanced multi-robot coordination.
Roulette Genetic Algorithm [50]	Inventory Forecasting	Demand prediction within DT for seasonal planning.	Improved demand estimation, better stock control.
Deep Learning (YOLOv3) [54]	Object Recognition	Visual inspection and goods detection using DT.	Faster detection, reduced manual errors.
MILP + ABC [56]	Task Scheduling	DT-based robot task scheduling and dependency modeling.	Reduced delays, balanced workload distribution.
Auction Algorithm + D* Lite [92]	Real-Time Coordination	Conflict-aware task assignment and routing in DT.	Reduced energy usage, improved throughput.
RFID + PSO/LMS [80,82]	Localization	DT simulation for 3D object/robot localization using RFID.	Higher accuracy, real-time traceability.
Federated Learning (FL)	Distributed Model Training	Collaborative DT-based model training without raw data exchange.	Secure cross-site learning, enhanced privacy.
MILP Optimization [84–86]	Storage Assignment, Fleet Sizing	DT simulation for space assignment and fleet sizing.	Reduced costs, optimized layout and fleet efficiency.
DRL framework [89]	AGV task allocation in smart warehouses	Simulates AGV states and tasks for training/testing	Reduces empty travel, improves resource use, and real-time decision-making.

fall short of handling the complexity brought by real-time demands, high customer expectations, and increased digitalization. To overcome these limitations, warehouses are increasingly integrating Artificial Intelligence (AI) techniques with Digital Twin (DT) technologies, significantly enhancing the optimization of various operational tasks. Fig. 11

illustrates a representative framework demonstrating how physical entities, Digital Twin models, IoT-based data acquisition, and advanced AI technologies interact in a cohesive workflow.

The framework represents an advanced system where physical warehouse operations and Digital Twin simulations operate concurrently.

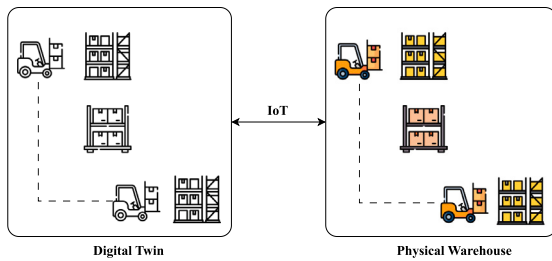


Fig. 5. Dynamic path planning and routing of AVG's.

The flow begins with the physical entities, including AGVs, robots, and warehouse inventory systems, which generate real-time operational data. IoT devices collect these data, using sensors and cloud storage systems for seamless acquisition and secure storage. Subsequently, this data flows into a centralized processing unit where various AI methodologies including Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), Federated Learning (FL), and Reinforcement Learning (RL) analyze and interpret it. These AI-driven insights optimize warehouse operations by predicting demand, managing inventory efficiently, coordinating robotic tasks, and planning paths dynamically. The Digital Twin utilizes these insights to simulate warehouse scenarios, enabling proactive decision-making and continuous improvement in real-time. Table 3 presents an overview of AI-based techniques that enhance Digital Twin-based warehouse systems.

The following subsections outline how AI is utilized to tackle key challenges in warehouse logistics systems, focusing on the integration with Digital Twin technology to enhance overall warehouse performance. As depicted in Fig. 6, the framework clearly maps significant warehouse operational problems such as path planning, task allocation, and real-time coordination to corresponding AI-driven solutions.

3.1. Dynamic path planning and routing optimization

Path planning is one of the most critical tasks in warehouse logistics, ensuring that goods move efficiently from one location to another. In modern warehouses, automated guided vehicles, robotic systems, and other autonomous vehicles must navigate complex layouts with minimal delays and zero collisions. Optimizing the movement of these systems is key to reducing operational costs and improving throughput.

AI-driven solutions have been particularly successful in this domain. Zhang et al. [49] proposed an innovative Q-learning-based technique designed specifically for multi-AGV routing in large-scale warehouse environments. This approach factors in variables such as load status, route turns, and real-time collision avoidance. Their method demonstrated significant improvements, including reduced travel time (by 10 s), enhanced efficiency (by more than 11 percent), and reduced energy consumption in multi-AGV operations. Additionally, Tang et al. [50] introduced a Digital Twin-based framework for inventory management and demand forecasting. By integrating a roulette genetic algorithm into their model, they were able to predict demand accurately and manage inventory levels effectively. This framework helped mitigate the impact of economic fluctuations and seasonal changes, providing warehouses with valuable insights to optimize stock levels.

In context of Fig. 5 dynamic path planning for AGVs within a warehouse, the system's state at any given time t is defined by a variety of factors that are continuously updated through the Digital Twin. These factors include the AGV's position within the warehouse, its load status, and the surrounding environment, such as the presence of obstacles and traffic conditions. Based on these real-time updates from the Digital Twin, the AGV makes a decision about the next action to take (i.e., its path or movement).

Each action taken by the AGV, represented as a_t , results in a reward r_t , based on the feedback from the Digital Twin, which may account

for variables such as minimized travel time, collision avoidance, or energy consumption. The goal of the AGV, using Q-learning, is to maximize the cumulative reward by making decisions that optimize its route over time. To model this, Q-learning operates by evaluating and updating a Q -value for each state–action pair $Q(s_t, a_t)$. This value represents the expected cumulative reward from taking action a_t at state s_t , considering both immediate rewards and the potential for future rewards. At each time step t , after the AGV takes an action a_t , it transitions to a new state s_{t+1} , which is again updated by the Digital Twin based on the real-time data. The Q -value for the state–action pair (s_t, a_t) is updated using the following formula:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right]$$

Where, $Q(s_t, a_t)$ represents the expected cumulative reward for taking action a_t at state s_t . The term r_t denotes the reward received after performing action a_t in state s_t , which is derived from real-time feedback provided by the Digital Twin, such as the efficiency of movement or the amount of energy consumed. The discount factor γ determines how future rewards are weighted relative to immediate ones, while the learning rate α controls the extent to which new information updates the existing Q -value. Finally, $\max_{a'} Q(s_{t+1}, a')$ represents the maximum estimated Q -value for the next state s_{t+1} , considering all possible actions a' that could be taken from that state.

This update rule allows the AGV to iteratively learn and refine its path planning strategy by balancing the trade-off between immediate rewards and long-term optimization. As the AGV receives real-time updates from the Digital Twin, it adapts its decision-making process to navigate the warehouse efficiently, minimizing travel time, avoiding obstacles, and optimizing energy usage.

3.2. AI-based multi-robot coordination and task allocation

Efficient coordination of multi-robot systems is a major challenge in smart warehousing. Given the dynamic and often unpredictable nature of warehouse operations, task allocation plays a critical role in ensuring that robots work efficiently without delays. In complex environments, improper task allocation can lead to inefficiencies, idle time, and bottlenecks in operations.

Zhao et al. [52] introduced a hierarchical GA-ACO (Genetic Algorithm-Ant Colony Optimization) model to improve task allocation in multi-robot systems. By accounting for environmental constraints and optimizing task distribution, their method resulted in significantly shorter transportation times and enhanced coordination between robots. In a simulated warehouse setting, this model was able to plan tasks more efficiently for a team of robots, thus improving operational throughput. Agrawal et al. [53] took a different approach by developing RTAW, a reinforcement learning-based method that improves multi-robot coordination. RTAW showed impressive results, including a 14 percent performance boost compared to traditional task allocation methods. This success highlights the growing trend of incorporating machine learning models for adaptive decision-making in complex, real-time logistics environments.

Li et al. [89] proposed a deep reinforcement learning (DRL) framework to address task allocation among heterogeneous automated guided vehicles (AGVs) in smart warehouses. They introduced the capacitated multiagent open pickup and delivery problem (CMOPDP), which allows vehicles to start from different locations and avoids unnecessary returns to depots, reflecting realistic warehouse operations. Their method uses an encoder–decoder architecture with heterogeneous attention to capture vehicle-node relationships, dual decoders for cooperative decision-making, and entropy rewards to improve exploration and prevent local optima. Experimental results demonstrated that their framework improves solution quality by at least 1.76% over existing heuristic and DRL baselines while maintaining competitive computation time. This work illustrates the emerging

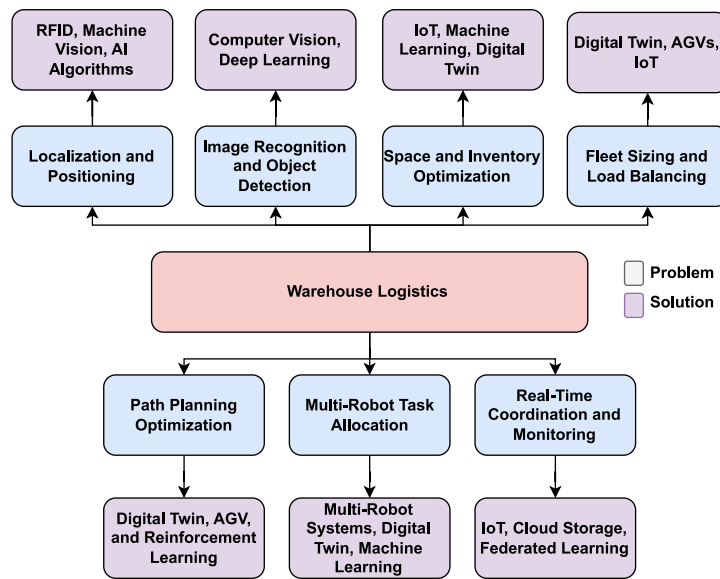


Fig. 6. Digital Twin in warehouse logistics AI-based problem-solution mapping.

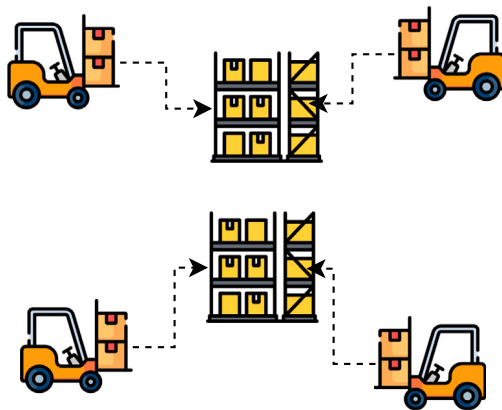


Fig. 7. Multi robot coordination and task allocation.

trend of employing DRL to handle complex, real-time task allocation problems in large-scale, multi-agent warehouse environments, though challenges remain in training efficiency, convergence in dense settings, and multiobjective optimization.

Demonstrated in Fig. 7, in a warehouse environment multiple AGVs must operate concurrently, coordinating their movements and tasks to maximize overall efficiency while avoiding collisions and delays. Consider an AGV navigating from a start to a goal in the presence of dynamic obstacles: the AGV state s_t comprises its pose and the set of obstacle observations provided by onboard sensors and the DT. Path replanning in such settings is efficiently handled by the incremental D* Lite algorithm, which maintains a cost-to-go function $h(s)$ and updates it when the environment changes. The incremental update is compactly written as

$$h(s) = \min_{s'}(c(s, s') + h(s')),$$

where $c(s, s')$ denotes the transition cost from state s to successor s' . This update rule allows the AGV to revise only the affected portion of the plan when new obstacles are observed, thereby producing conflict-aware, low-latency path adjustments.

Task allocation among multiple AGVs is handled concurrently with path planning. In an auction-based scheme each robot i places a bid for task t based on its proximity and expected energy cost, so that tasks

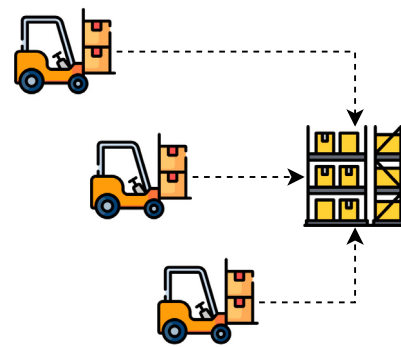


Fig. 8. Warehouse operation localization and detection.

are assigned to robots that can complete them most efficiently. A simple normalized bid model is

$$b_i = \alpha \left(\frac{1}{\text{distance}(i, t)} + \frac{1}{\text{energy_cost}(i)} \right),$$

where $\text{distance}(i, t)$ is the travel distance from robot i to task t , $\text{energy_cost}(i)$ is the estimated energy required, and α is a scaling factor. The auctioneer assigns each task to the robot with the highest bid (or lowest composite cost), and the system re-auctions tasks as conditions change, ensuring that task distribution remains adaptive and efficient in a dynamic multi-robot warehouse. (see Figs. 8 and 9).

3.3. AI and Digital Twin for real-time coordination

The combination of AI techniques with Digital Twin technologies enhances warehouse efficiency by facilitating real-time simulations and decision-making. Digital Twins, which create a dynamic, digital replica of a warehouse, enable continuous monitoring and optimization of operations. By integrating AI models with these virtual replicas, warehouses can adapt instantly to changes in demand, equipment availability, and operational constraints.

Mei et al. [92] addressed the challenge of path planning and task allocation by developing a hybrid framework that integrates an upgraded market auction algorithm for job assignment with a D* Lite-based algorithm for conflict-aware path planning. This integrated solution optimized routing and task distribution, significantly reducing travel time

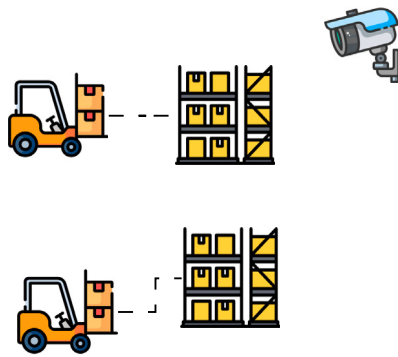


Fig. 9. Warehouse operation localization and detection.

and energy costs, particularly in densely packed shelf environments. Shi et al. [93] also developed an integrated system that combines real-time robot density estimation with auction-based task allocation. Their method utilizes collision avoidance protocols and the Floyd algorithm to further optimize routing. The results from their simulations, involving up to 100 robots, showed a substantial reduction in task completion time and improved system throughput, demonstrating the power of integrating AI with Digital Twin technologies in a multi-robot warehouse environment.

In a warehouse environment with N autonomous robots, each robot i is assigned a task a_i predicted by the Digital Twin to require a travel distance D_i , time T_i , and energy E_i . To evaluate assignments, the Digital Twin computes a cost function that combines these factors, expressed as

$$J_i = w_d D_i + w_t T_i + w_e E_i,$$

where w_d , w_t , and w_e are weighting coefficients reflecting the relative importance of distance, time, and energy efficiency. The AI-based allocator then selects the assignment set $\{a_i\}$ that minimizes the total system cost,

$$\min_{\{a_i\}} \sum_{i=1}^N J_i,$$

enabling real-time coordination and adaptive optimization through continuous feedback from the Digital Twin.

3.4. AI-driven localization and image recognition

Accurate localization and image-based recognition systems are essential in modern warehouses for ensuring the efficient execution of tasks such as item identification, inventory tracking, and damage detection. AI has proven to be instrumental in solving the challenges posed by real-time localization and dynamic object recognition, especially in complex and constantly changing environments. Tripicchio et al. [82] and Yang et al. [80] focused on solving the localization problem by using RFID technology integrated with intelligent algorithms. Tripicchio's work leveraged real-time RFID data and an enhanced Particle Swarm Optimization (PSO) algorithm to optimize warehouse location assignments. Meanwhile, Yang et al. used algorithms based on least mean squares to improve the accuracy of robot motion planning through enhanced object positioning in a 3D space.

In the realm of object recognition, He et al. [54] worked on enhancing the capabilities of object detection models for industrial environments. They improved the YOLOv3 (You Only Look Once version 3) deep learning model to increase detection speed and accuracy in the warehouse setting. This improvement has significant implications for automating tasks such as inventory management, damage detection, and quality control, reducing the need for manual intervention.

Fig. 10 shows that warehouse, accurate localization, and real-time image recognition are essential for tasks such as inventory tracking and item identification. Imagine a robot tasked with navigating a warehouse to locate specific items while avoiding obstacles. Localization ensures that the robot knows its position within the warehouse, while image recognition allows it to identify objects. For localization, RFID technology combined with an optimization algorithm like PSO can be used to refine the robot's position. The PSO algorithm minimizes the location error by iteratively adjusting the robot's estimated position based on the feedback from RFID tags. The position p at time t is optimized using the following objective function:

$$\text{Minimize } f(p) = \sum_{i=1}^n (w_i \cdot \|p_i - p\|^2)$$

Where $f(p)$ represents the location error, p_i is the true position, and w_i is the weight for each tag. For image recognition, YOLOv3 can be used to detect and classify objects in real-time. The model predicts object labels \hat{y}_i , and the cross-entropy loss is used to optimize its performance by comparing predicted labels with true labels:

$$\mathcal{L}(y_i, \hat{y}_i) = - \sum_{i=1}^n y_i \log(\hat{y}_i)$$

Where $\mathcal{L}(y_i, \hat{y}_i)$ is the loss function, y_i is the true label, and \hat{y}_i is the predicted label. By minimizing this loss, the robot improves its object detection accuracy, essential for tasks like inventory management and damage detection. By integrating RFID localization and YOLOv3 image recognition, the robot can navigate effectively and identify items accurately, automating warehouse operations and reducing manual effort.

3.5. Task planning and scheduling optimization in multi-robot systems

Coordinating multiple robots to perform tasks in an efficient and timely manner is a complex but essential aspect of modern warehousing. AI plays a central role in developing solutions that intelligently assign tasks and plan robot schedules, minimizing delays, energy consumption, and operational bottlenecks.

Zhuang et al. [56] tackled this issue by using Mixed-Integer Linear Programming (MILP) and hybrid Artificial Bee Colony (ABC) optimization to plan and schedule tasks for multi-robot systems. Their study showed how task execution time could be reduced by managing complex scheduling and task dependencies. Their approach demonstrated efficiency in real-world warehouse scenarios, where the environment constantly changes due to variations in workload. Bolu and Korcak [55] proposed an Adaptive Task Planning (ATP) model for Robotic Mobile Fulfillment Systems (RMFS). This approach used a centralized task management algorithm that could respond dynamically to changes in warehouse operations, such as fluctuating order volumes or robot availability. Through extensive simulations, they found that their adaptive task management system significantly reduced order fulfillment times and balanced workloads across robots, even when dealing with large inventories.

In multi-robot systems, task planning and scheduling are essential for ensuring efficient coordination among robots. The challenge is to assign tasks to robots in a way that minimizes the overall completion time, while avoiding conflicts such as task overlaps or robot collisions. The goal is to optimize both the assignment of tasks and the schedule, ensuring that tasks are completed in the shortest time possible. The problem can be formulated using a MILP approach, where x_{ijt} is a binary variable that equals 1 if robot i is assigned to task j at time t . The objective is to minimize the total makespan, which is the total time taken to complete all tasks:

$$\text{Minimize } Z = \sum_{i=1}^n \sum_{j=1}^m \sum_{t=1}^T x_{ijt} \cdot t$$

Table 4
Existing benchmark warehouse logistics evaluation datasets.

Dataset	Type & scale	Application domain	Key features
MAPF-Word [94]	Multi-Agent Path Finding 100–1000 agents, multiple map types Grid sizes: 32× 32 to 1024× 1024	AGV path planning, collision-free routing, multi-agent coordination testing	Publicly available, widely adopted standard, diverse scenarios, scalability testing
COHERENT [95]	Heterogeneous Multi-Robot 100 tasks (mono/dual/trio-type) 5 scenes, 3 robot types	Multi-robot collaboration, heterogeneous coordination, dynamic task allocation	Realistic warehouse scenarios, standardized evaluation protocol, diverse task complexity
3D Warehouse MAPF [96]	3D Multi-Level Path Finding Multi-floor structures Vertical transport, 100+ agents	Complex multi-level warehouse path planning, vertical navigation, elevator coordination	Three-dimensional routing, realistic warehouse constraints, elevator integration
ARMBench [97]	Robotic Pick-and-Place 190,000+ objects 4000 defect videos	Object segmentation, identification, defect detection, manipulation quality assessment	Largest industrial pick-place dataset, real warehouse conditions, multi-task annotations
Amazon Picking Challenge Dataset [98]	Warehouse Item Picking 25 common objects Shelf picking scenarios	Robotic grasping, object recognition, bin picking, manipulation planning	Industry-standard benchmark, diverse object categories, realistic clutter
COCO Dataset [99]	Object Detection & Segmentation 330,000 images, 80 categories 200,000+ labeled images	Warehouse object detection, item recognition, computer vision training	Large-scale annotations, semantic segmentation support, widely adopted standard
KITTI Dataset [100]	Visual Navigation & Odometry Laser scans, camera images GPS/IMU data	Indoor warehouse navigation, visual odometry, SLAM applications	Multi-sensor fusion, precise ground truth, navigation benchmarking
BEHAVIOR-1K [101]	Embodied AI & Task Planning 1000 everyday activities Warehouse-relevant scenes	Task planning, embodied AI, human–robot collaboration scenarios	Activity-centric annotations, realistic scenes, long-horizon planning
Warehouse Box Detection [102]	Object Detection for Logistics Delivery boxes, various conditions Diverse orientations	Box detection, automated sorting, inventory management	Warehouse-specific objects, real-world variability, practical application focus.

This formulation is subject to constraints such as each task j being assigned to exactly one robot, each robot performing only one task at a time, and ensuring that tasks are completed within their respective time windows. By optimizing these variables, the system can efficiently schedule tasks, reducing overall time and improving robot coordination in dynamic environments.

3.6. AI-driven optimizing warehouse space and inventory

As warehouses move towards automation and AI-driven systems, optimizing space utilization and inventory management becomes crucial. Traditional warehouse systems often struggle with space allocation and inventory balancing, leading to inefficiencies in product retrieval and storage. AI-based models integrated with Digital Twin technologies can solve these problems by providing real-time insights into inventory levels and available storage space.

Zhang et al. [84] developed an AI-based system for optimizing storage assignment in warehouses, particularly in industries like food production. Their system integrated production planning with storage allocation using a Mixed-Integer Linear Programming (MILP) model. This approach helped improve space utilization, reduce operational costs, and maintain optimal stock levels. The integration of IoT devices further enabled real-time monitoring of inventory and dynamic adjustments to storage assignments based on fluctuating demand. Rjeb et al. [85] focused on fleet-sizing problems, developing an MILP model to optimize robot fleets for transporting goods between storage locations. Their model balanced cost-efficiency with performance, helping warehouses determine the optimal number of robots required for specific tasks. This optimization model facilitates the integration of Digital Twin-based simulations that can adjust fleet sizes dynamically in real-time. Leng et al. [86] introduced a Digital Twin-driven optimization technique for packing and storage assignments in high-rise automated warehouses. By combining sensor data with cyber–physical models, their system enabled continuous optimization of both packing and storage processes. Their research revealed significant improvements in space usage and system efficiency, demonstrating how AI and Digital Twin integration can enhance warehouse operations.

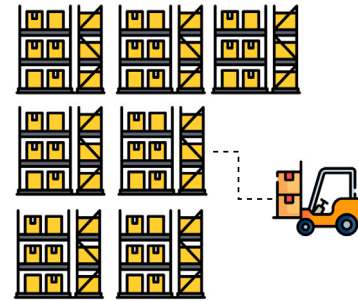


Fig. 10. Warehouse space and inventory optimization.

In a dynamic warehouse environment, efficient space utilization and inventory management are crucial to maximizing throughput and minimizing operational costs. As products' demand fluctuates, the task of assigning inventory to storage bins becomes more complex. The goal is to assign products to bins in such a way that both space utilization is maximized and retrieval times are minimized. AI-driven approaches, particularly RL, can help automate and optimize this process. By receiving real-time feedback from the warehouse, such as changes in product demand and space availability, the RL agent learns to adjust storage assignments dynamically, ensuring optimal storage while meeting demand efficiently.

To model this, let s_t represent the state of the system at time t , which includes factors like current product demand and available space in bins. The agent's action, a_t , refers to the decision to allocate products to specific bins. Based on these actions, the agent receives a reward r_t , which is based on factors like space utilization and the ability to meet product demand. The objective of the RL model is to maximize the cumulative reward by refining the policy over time. The agent updates its Q-values using the standard Q-learning update rule:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right]$$

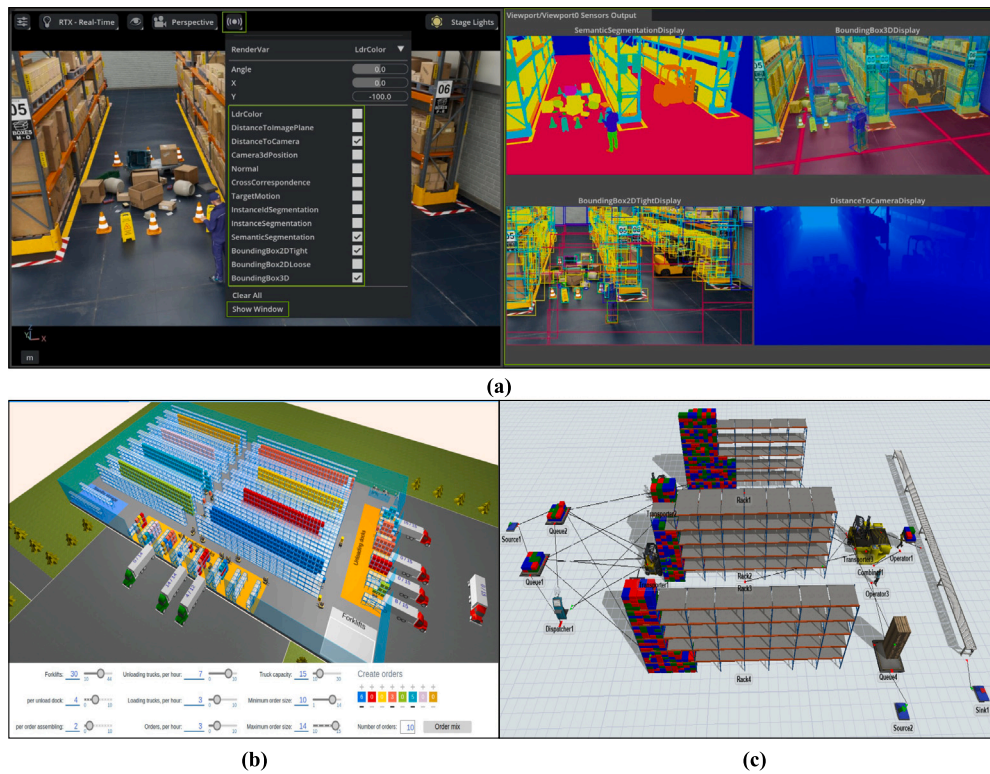


Fig. 11. Warehouse logistics Digital Twin simulation using (a) Omniverse Isaac Sim, (b) AnyLogic, and (c) FlexSim.

In this formula, $Q(s_t, a_t)$ represents the expected reward of taking action a_t at state s_t , α is the learning rate, r_t is the immediate reward, and γ is the discount factor, representing the importance of future rewards. The term $\max_{a'} Q(s_{t+1}, a')$ reflects the maximum expected future reward for the next state. By continuously updating the Q-values, the RL agent learns to allocate products to storage bins in an optimized manner, balancing space usage with demand fulfillment.

4. Simulation, datasets and evaluation

4.1. Warehouse logistics digital twin simulation

Platforms such as NVIDIA Omniverse, AnyLogic and FlexSim are frequently employed in DT engineering to simulate complex warehouse environments. These tools allow for the modeling of logistics operations, including the optimization of AGV path planning, inventory management, and task allocation, providing a realistic testing ground before deploying real-world solutions.

NVIDIA Omniverse. Isaac Sim is a high-fidelity simulation platform for creating and testing digital twins of robotic and industrial systems. Built on Omniverse and leveraging OpenUSD (Universal Scene Description), it enables construction of complex 3D environments with precise geometry, materials, lighting, and physics. Users can simulate robot dynamics, sensor noise, collisions, and environmental variability (Fig. 11a). Isaac Sim supports various sensors such as LiDAR, RGB-D cameras, IMUs, and tactile sensors to generate multi-modal datasets for AI model training and control validation. Programmatic access via Python and the Omniverse Kit API allows automated experiments, scenario randomization, and data export for machine learning and optimization studies.

The platform produces diverse data types including images, depth maps, point clouds, joint states, forces, torques, and collision logs—enabling analysis of kinematics, energy efficiency, and task performance. Its domain randomization capability improves model robustness, making Isaac Sim ideal for real-world deployment in research and industrial digital twins.

Synthetic Data Generation in Isaac Sim. NVIDIA Omniverse Isaac Sim provides a comprehensive Synthetic Data Generation (SDG) ecosystem that enables the creation of high-quality, annotated datasets for robotics, AI, and industrial applications. This ecosystem supports perception, manipulation, and mobility tasks by simulating realistic physical and visual conditions within controlled 3D environments.

The Replicator extension serves as the core framework for perception-based data generation. It automates the process of rendering, labeling, and domain randomization, allowing users to vary lighting, textures, and object arrangements to improve model robustness. Replicator supports the generation of large-scale datasets with RGB, depth, and segmentation outputs, making it essential for training computer vision and reinforcement learning models.

The IRA (Interactive Robot and Actor) extension focuses on human-robot interaction. It enables realistic motion control for both human and robotic agents and produces synchronized multi-modal outputs – such as RGB, depth, and stereo imagery – useful for studying collaborative robotics, warehouse automation, and safety assessment.

The Grasping SDG module provides a structured pipeline for robotic manipulation. Users can define gripper types, target objects, and grasp configurations, simulate contact dynamics, and collect outcome data for algorithm training and validation.

Finally, MobilityGen extends SDG capabilities to mobile robots, supporting trajectory planning, occupancy mapping, and navigation scenario replay. Together, these GPU-accelerated modules – Replicator, IRA, Grasping SDG, and MobilityGen – enable scalable, diverse, and realistic dataset generation, significantly reducing the cost and risk of real-world data collection while enhancing AI and digital twin development.

Collectively, these GPU-accelerated tools – Replicator, IRA, Grasping SDG, and MobilityGen – enable efficient generation of diverse, realistic, and annotated datasets for robotics, AI, and digital twin engineering while minimizing real-world risks and costs.

AnyLogic is a versatile, multi-method simulation platform widely used for modeling and analyzing complex industrial and socio-technical

Table 5
Comprehensive evaluation metrics for warehouse logistics performance assessment.

Category	Metric	Definition	Unit	Application domain
Efficiency	Makespan	Total time to complete all assigned tasks	Seconds/minutes	Task scheduling, multi-robot coordination
	Throughput	Orders or items processed per unit time	Orders/hour	Overall warehouse performance assessment
	Travel Time/Distance	Total AGV/robot movement during operations	Seconds/meters	Path planning evaluation, energy assessment
	Order Completion Time	Time from order receipt to fulfillment	Minutes/hours	End-to-end performance, customer satisfaction
	Cycle Time	Time for one full operational cycle	Seconds	Process optimization, bottleneck identification
	Task Completion Rate	Tasks successfully completed in timeframe	Tasks/hour	Productivity assessment, capacity planning
Quality	Waiting Time	Time robots wait due to conflicts	Seconds	Coordination efficiency, congestion analysis
	Success Rate	Percentage of tasks completed successfully	Percentage	System reliability, algorithm robustness
	Collision Rate	Frequency of collisions between robots	Collisions/hour	Safety assessment, coordination effectiveness
	Accuracy	Precision of picking/localization operations	Percentage	Quality assurance, system precision
	Localization Error	Mean positioning error in 2D or 3D space	Centimeters	Navigation precision, RFID evaluation
	Pick Accuracy	Correctly picked items vs. total items	Percentage	Order fulfillment quality, picking evaluation
	Multipick Error Rate	Picking multiple items when one required	Errors/1000 picks	Grasping quality, manipulation precision
Resource	Detection Accuracy (mAP)	Mean Average Precision for object detection	mAP@IoU	Computer vision evaluation, recognition
	False Positive/Negative Rate	Rate of incorrect or missed detections	Percentage	Vision reliability, anomaly detection quality
	Utilization Rate	Active working time vs. total available time	Percentage	Resource efficiency, capacity planning
	Energy Consumption	Energy consumed during operations	kWh or Wh/task	Sustainability, operational cost evaluation
	Space Utilization	Warehouse space effectively used	Percentage	Storage optimization, layout assessment
	Fleet Size Efficiency	Actual vs. minimum theoretical fleet size	Ratio	Fleet optimization, capital efficiency
Computational	Battery Efficiency	Working time per charge or energy per task	Hours/charge	Battery management, operational continuity
	Idle Time	Time robots remain idle without tasks	Percentage	Task allocation efficiency, load balancing
Scalability	Computation Time	Time to compute planning solutions	Milliseconds/seconds	Algorithm scalability, real-time capability
	Solution Quality	Gap from optimal solution or baseline	Percentage	Algorithm performance, optimization effectiveness
Robustness	Agent Scalability	Maximum agents system can handle	Number of agents	System scalability, deployment feasibility
	Map Size Scalability	Maximum map dimensions processable	Grid cells/m ²	Large warehouse applicability, complexity
Safety	Generalization Capability	Performance on unseen scenarios	Percentage of baseline	Learning algorithm evaluation, adaptability
	Failure Recovery Time	Time to recover from failures/deadlocks	Seconds	System resilience, fault tolerance
Economic	Near-Miss Rate	Close encounters without collision	Events/hour	Safety margin evaluation, proactive safety
	Deadlock Frequency	Deadlock situations requiring intervention	Events/hour	Coordination robustness, safety-critical
Economic	Cost per Operation	Average cost to complete one task	Currency/operation	Economic efficiency, ROI calculation
	Payback Period	Time to recover initial investment	Months/years	Investment justification, financial planning

systems. Unlike physics-based tools such as NVIDIA Omniverse Isaac Sim, which emphasize detailed physical interactions, AnyLogic focuses on process-driven and behavioral modeling, making it ideal for logistics, manufacturing, and supply-chain digital twin applications. It uniquely integrates discrete-event simulation (DES), agent-based modeling (ABM), and system dynamics (SD) within a single framework, enabling users to represent both micro-level operations and macro-level system dynamics.

In digital twin contexts, AnyLogic models real-time process flows, resource utilization, and decision-making logic by synchronizing simulation variables with IoT and sensor data. This supports predictive analytics, what-if analysis, and operational optimization without the computational cost of 3D physics simulation. Through agent-based modeling, entities such as robots, workers, and vehicles can be modeled as intelligent agents that interact according to probabilistic rules, enabling the study of multi-agent coordination, task allocation, and human-robot collaboration.

Its discrete-event simulation component provides a detailed representation of workflows such as order picking, assembly, and transportation routing, making it well suited for warehouse management and production optimization. Built-in experiment types – such as Parameter Variation, Monte Carlo, and Optimization – allow systematic evaluation of system performance indicators, including throughput, resource utilization, and lead time.

AnyLogic also provides interactive 3D visualization and animation (Fig. 11b) for representing material flows, agent movements, and production dynamics. Although less realistic than Omniverse, it provides effective spatial awareness for decision-making and stakeholder communication. The Material Handling and Process Modeling Libraries further extend its capabilities to simulate conveyor systems, AS/RS equipment, and workforce allocation.

Simulation outputs, including event logs, queue lengths, and resource states, can be exported for use in AI pipelines and optimization

models. With AnyLogic Cloud, users can conduct distributed simulations and monitor system performance in real time. Overall, AnyLogic complements high-fidelity platforms like Isaac Sim by emphasizing behavioral accuracy, process logic, and system-level intelligence in digital twin development.

FlexSim. FlexSim is a powerful industrial simulation platform used in Digital Twin applications to create virtual models of warehouse environments. By integrating real-time data from IoT devices, it allows for the simulation and optimization of warehouse operations such as AGV routing, task allocation, and inventory management. To simulate FlexSim in a warehouse environment illustrate in (Fig. 11c) that incorporates various elements such as racks, conveyor systems, transporters, queues, and operators. In the simulation, racks are used to store goods, and the transporters autonomously move items between different locations in the warehouse, such as from queues to racks or vice versa. The queues hold goods temporarily, either awaiting processing or shipment, while the operators assist with tasks requiring human intervention, such as sorting or managing the movement of goods. The integration of conveyor systems further supports the movement of goods between various points in the warehouse. By combining AI with FlexSim, warehouses can achieve autonomous decision-making and continuous real-time optimization, ultimately improving efficiency, reducing costs, and enhancing overall performance. The simulation allows us to model how these elements interact in real-time to optimize workflows, test different operational strategies, and improve warehouse efficiency and resource utilization. All of these processes are coordinated within FlexSim to streamline operations and ensure smooth, efficient ware-house management.

4.2. Datasets

Several benchmark datasets mentioned in Table 4 are commonly used for evaluating algorithms in warehouse logistics optimization. The MAPF-Word Benchmarks are widely recognized for AGV path planning,

supporting scalability testing with 100–1000 agents and varying grid sizes. For multi-robot task allocation, the COHERENT Benchmark offers scenarios with heterogeneous robots and dynamic task assignments, while the 3D Warehouse MAPF Dataset introduces the complexity of multi-level warehouse layouts with vertical transport. The MAPF-World dataset provides large-scale training data with real-world urban layouts, ideal for learnable MAPF solvers.

In terms of object detection and manipulation, the ARMBench (Amazon) dataset, which includes over 190,000 objects and 4000 defect videos, is critical for robotic pick-and-place tasks. Similarly, the Amazon Picking Challenge Dataset is used for testing robotic grasping and bin picking. The COCO Dataset is commonly adapted for warehouse object recognition tasks due to its large-scale annotations and support for segmentation. Additionally, datasets like SafeLog MAPF focus on industrial AGV path planning and safety-critical environments, while Real Industry Warehouse Data from companies like Amazon and DHL provide real-world validation with actual warehouse layouts and historical operational data. These datasets provide comprehensive resources for testing warehouse operations environments in both simulated and real-world warehouse environments, enabling performance benchmarking across various logistics tasks.

4.3. Evaluation criteria

Table 5 summarizes the primary evaluation metrics used to assess warehouse logistics algorithms and systems. The metrics are organized into thematic categories: Efficiency (e.g., makespan, throughput, travel distance), Quality (e.g., success rate, collision rate, localization error), Resource (e.g., utilization, energy consumption, space utilization), Computational (e.g., computation time, solution quality), Scalability, Robustness, Safety, and Economic measures each targeting a distinct aspect of system performance. Together these indicators enable comprehensive benchmarking of path planning, task allocation, perception and resource-management methods: efficiency and quality metrics measure operational effectiveness and reliability; resource and economic metrics capture cost and sustainability implications; and computational, scalability and robustness metrics evaluate algorithmic feasibility for real-time, large-scale deployment.

5. Research gaps and future directions

The previous sections have critically analyzed the existing literature on the application of optimization approaches to solve operational warehouse problems in the era of digital transformation. These reviews explored the present application of Artificial Intelligence in digital twin systems for warehouse logistics. It featured cutting-edge models for real-time tracking, path optimization, robots, demand forecasting, and predictive maintenance. However, most current research focuses on single-warehouse situations and does not investigate how AI-powered digital twins behave in complicated, multi-node supply networks. Few studies investigate how real-time AI decisions in DTs impact long-term warehouse efficiency. Furthermore, most DT models employ predefined rules rather than learning from continual feedback.

To implement the conceptual AI-Digital Twin (AI-DT) warehouse framework, we summarize seven high-impact research directions in Table 6. Each direction is characterized by a clearly defined problem, the corresponding technical mechanism, implementation stack, and supporting empirical evidence. The directions are organized according to maturity and potential impact, ranging from immediately deployable approaches (e.g., Edge AI with Federated Learning) to more transformative but currently constrained technologies (e.g., Quantum Computing integrated with 6G). In particular, all directions incorporate real-world validation, from simulation benchmarks to industry pilot studies, ensuring that the table reflects practical feasibility rather than speculative proposals.

5.1. Real-time implementation

While digital twins provide real-time monitoring capabilities, their integration with AI in warehouse logistics is frequently hampered by computational complexity and data latency. Future research should look toward edge AI frameworks that enable on-device processing for real-time optimization while lowering reliance on cloud infrastructure. This is especially important for small to medium-sized warehouses with limited computational resources [107]. For example, edge AI could improve robotic picking routes in real time, reducing energy usage and operating delays.

Furthermore, the lack of established protocols for AI-DT integration limits scalability. Researchers should concentrate on creating interoperable frameworks that enable seamless data interchange between AI algorithms, digital twins, and warehouse management systems. One potential path is to employ federated learning to train AI models across remote warehouse networks while ensuring data privacy and addressing regulatory constraints in global supply chains.

5.2. Sustainability and human-centric optimization

Sustainability is an important but underexplored component of AI-powered digital twin applications in warehouse logistics. Existing research focuses exclusively on operational efficiency, frequently ignoring environmental implications [108]. Future study could look into AI-optimized digital twins for green logistics, such as reducing carbon emissions via energy-efficient routing or predictive maintenance of electric warehouse cars. Reinforcement learning, for example, could be used to balance delivery speed versus energy usage in autonomous guided vehicles. In addition, human-AI collaboration in warehouse logistics is still in its early stages. Digital twins might serve as interactive training platforms for human operators, with augmented reality (AR) interfaces driven by AI providing real-time assistance. Research should look into how AR-enhanced digital twins can increase worker safety and efficiency, especially while handling dangerous or perishable commodities [109].

Goods-to-person (GTP) automation systems, which streamline order fulfillment and warehouse navigation, have received limited attention in the context of AI and digital twins [110]. Digital twins can simulate GTP workflows, while AI can optimize picking routes and resource allocation. Future studies should investigate AI-driven digital twins for GTP optimization, focusing on reducing picking errors and improving navigation efficiency in large-scale warehouses. For instance, deep learning models could predict optimal GTP configurations within a digital twin, enhancing order fulfillment speed. This direction addresses the gap in exploring GTP systems and their impact on warehouse performance [111,112].

5.3. Transparency and efficiency

The integration of blockchain technology with AI and digital twins for warehouse logistics is a somewhat unexplored topic. Blockchain technology can improve the transparency and security of the data used by digital twins, especially for inventory management and supply chain tracking [113]. Future studies should look at AI blockchain-DT frameworks to boost efficiency, reduce costs, and maintain data integrity in warehouse operations. For example, AI may examine blockchain-secured data within a digital twin to optimize inventory replenishment cycles, bridging the transparency-driven optimization gap.

To address the need for more concrete applications, the integration of blockchain, artificial intelligence, and digital twins (DT) can be implemented through targeted frameworks that enhance warehouse logistics. In the following, we outline specific use cases, implementation strategies, and potential benefits to provide actionable information for future research and deployment. Practical Applications of AI-Blockchain-DT Frameworks

Table 6
 Technical grounding and feasibility for future research in AI-Enabled Digital Twin warehouse systems.

Research direction	Concrete problem definition	Technical mechanism	Implementation strategy	Feasibility evidence & constraints
Real-Time Implementation via Edge AI & Federated Learning	High latency and computational overload in cloud-reliant AI-DT systems; lack of privacy-preserving, scalable training across distributed warehouses.	– Edge AI: On-device inference (e.g., path optimization) – Federated Learning (FL): Decentralized training with differential privacy	– TensorFlow Lite/PyTorch Mobile – on edge gateways – Flower/FLWR for FL orchestration – MQTT for WMS sync	Pilot simulations show 60%–80% latency reduction vs cloud-based AI-DT; GDPR-compliant and maintains model accuracy.[103]
Sustainability via Green Routing & Predictive Maintenance	Efficiency-focused AI ignores energy/carbon costs in routing and equipment use.	– Reinforcement Learning (RL): Multi-objective (speed vs. energy) – Predictive Maintenance: Sensor-based failure forecasting for electric AGVs	– Stable Baselines3/Ray RLlib in DT-IoT fusion (vibration, SoH) – Simulate via AnyLogic/Flexsim/Omniverse	Simulation experiments with heterogeneous AGV fleets show 24%–30% energy reduction in small to large warehouse scenarios.[104]
Human-Centric Optimization via AR-Enhanced DTs	Poor human–AI synergy; safety/training gaps in hazardous/perishable goods handling.	– AR Overlays: Real-time AI guidance – DT Simulator: Scenario-based training	– Unity + HoloLens or PTC Vuforia – OPC UA bidirectional sync	Laboratory and field prototyping showed improved training efficiency and significant reduction in handling errors. (Halldale)
Goods-to-Person (GTP) Optimization with AI-DTs	Static GTP configurations cause picking errors and navigation inefficiency in large warehouses.	– Deep Learning: CNN/RNN for layout/route prediction – DT Simulation: Virtual configuration testing	– Train on pick history; export via ONNX – Simulate in FlexSim/AutoMod	DT-based simulations with deep learning routing yielded 20%–30% reduction in picking errors in large-scale warehouses.[105]
Blockchain for Transparent & Automated Logistics	Lack of auditable, tamper-proof data for inventory provenance and automated replenishment.	– Smart Contracts: Threshold-triggered POs – Immutable IoT Logging: RFID + blockchain – AI Analytics on secured data in DT	– Hyperledger Fabric/Ethereum L2 – GS1 EPCIS for WMS integration – Pilot in pharma/perishables	Pilot projects show improved traceability and dispute reduction, with real-time inventory logs validated.
6G Networks for Real-Time Optimization	Connectivity loss and resource misallocation in dynamic, high-density mobile environments (robots/workers).	– Network Slicing: Task-priority bandwidth – AI Predictive Handover: ML trajectory forecasting – Sub-millisecond Streaming to DT	– Ericsson/Samsung 6G testbeds – MQTT/OPC UA integration – Federated learning at edge	Experimental 6G testbed results: 0.8 ms latency, ~15× faster than WiFi-6; supports 10× more devices than 5G; still constrained by 6G deployment availability.[106]
Quantum Computing for Advanced Optimization & Security	Intractable combinatorial problems (routing, layout); vulnerable DT data in global chains.	– DTQFL: Quantum federated learning for failure prediction – QAOA: Quantum optimization of logistics – DARIUS: Quantum key distribution	– IBM Qiskit/Azure Quantum (hybrid) – Cloud simulators for pilots – OPC UA API to WMS	Simulated QAOA experiments show 15%–25% reduction in downtime, ~99% drop in data breach risk; limited by current qubit counts and high hardware cost.

Real-Time Inventory Tracking and Provenance. The decentralized blockchain ledger can record every movement of goods, from supplier to warehouse to end customer, using unique identifiers such as RFID tags or QR codes. This ensures end-to-end transparency in inventory management. For example, in a warehouse that handles perishable goods, the blockchain can log temperature and humidity data from IoT sensors, creating verifiable trail. A digital twin can then visualize these data to monitor stock conditions in real time, while AI analyzes patterns to predict spoilage risks and optimize storage placement. This approach ensures compliance with regulations (e.g., the FDA Drug Supply Chain Security Act for pharmaceuticals) and reduces losses from expired goods.

Automated Inventory Replenishment with Smart Contracts. Smart contracts on a blockchain can automate inventory replenishment by triggering orders when a digital twin detects low stock levels. For example, if a digital twin of a retail warehouse indicates that a product’s inventory falls below a threshold, a smart contract can automatically issue a purchase order to a pre-verified supplier, with payment executed upon delivery confirmation. AI enhances this process

by forecasting demand based on blockchain-secured sales and logistics data, ensuring optimal order quantities. This reduces manual errors, accelerates replenishment cycles, and minimizes overstocking costs.

Optimized Warehouse Operations. AI can leverage blockchain-secured data within a digital twin to optimize internal warehouse processes. For example, machine learning algorithms can analyze historical picking data to recommend efficient routes for workers or robotic systems, reducing travel time within the warehouse. A digital twin can simulate different layouts to identify configurations that minimize bottlenecks, such as optimizing the placement of high-demand items near packing stations. Blockchain ensures that the data used (e.g., shipment arrival times, inventory counts) is tamper-proof, enabling reliable decision-making.

Predictive Maintenance for Warehouse Equipment. Blockchain can securely log operational data from warehouse equipment (e.g., forklifts, conveyor belts) collected via IoT sensors. A digital twin can model equipment performance, while AI analyzes this data to predict maintenance needs before failures occur. For example, if a conveyor belt’s vibration data indicates wear, AI can schedule maintenance

during low-activity periods, minimizing downtime. This approach, inspired by Amazon's predictive maintenance strategies, can reduce operational costs and improve efficiency.

Implementation Strategies. To operationalize AI-blockchain-DT frameworks, small-scale pilot projects in high-value sectors such as pharmaceuticals or perishable goods are recommended, integrating blockchain platforms like IBM's Hyperledger Fabric, digital twin solutions such as Siemens' MindSphere, and AI-based demand forecasting tools. Adoption of interoperability standards like GS1's EPCIS ensures that blockchain data is compatible with existing warehouse management systems (WMS) and AI tools, enabling seamless integration. Scalable and lightweight blockchain protocols, including Ethereum layer-2 solutions or Hyperledger, can reduce computational overhead and support real-time performance in large warehouses.

Expected Benefits. The integration of AI, blockchain, and digital twins can deliver significant benefits to warehouse operations. Automated replenishment and predictive maintenance reduce overstocking costs and equipment downtime, while AI-driven optimization of picking routes and warehouse layouts can improve throughput and operational efficiency. Blockchain ensures data integrity and full traceability, fostering trust among supply chain partners and minimizing disputes over inventory discrepancies. Furthermore, transparent and auditable records simplify compliance with industry regulations, lowering audit times and the risk of penalties, thereby creating a more secure and cost-effective logistics ecosystem.

5.4. 6G networks for real-time optimization

The integration of DTs with 6G networks promises to improve real-time monitoring and resource management in warehouse logistics. However, issues like as efficient resource allocation across twin-based IoT applications and ensuring connectivity during dynamic operations (e.g., mobile robots or workers) remain unexplored [23,114,115]. Future research should focus on developing AI-driven DT models for 6G-enabled warehouses, which will optimize inventory tracking and robotic navigation. For example, machine learning algorithms could forecast and reduce service disruptions by dynamically shifting DT services to new access points in response to worker or robot mobility.

To fully realize the potential of 6G-enabled AI-driven digital twin (DT) frameworks, specific applications and implementation strategies must be developed to address the challenges of resource allocation and connectivity in dynamic warehouse environments. The following sections outline practical use cases, deployment approaches, and future research directions to enhance real-time optimization, efficiency, and scalability in warehouse logistics. Practical Applications of 6G-Enabled AI-DT Frameworks:

High-Precision Real-Time Inventory Management. 6G networks, with their ultra-low latency (sub-millisecond) and high bandwidth (up to 1 Tbps), enable continuous data streaming from IoT devices such as RFID tags, cameras, and ultra-wideband (UWB) sensors to a digital twin. This creates a highly accurate, real-time model of inventory status. For example, in a large-scale e-commerce warehouse, 6G can support simultaneous tracking of thousands of items with centimeter-level precision, enabling AI algorithms (e.g., convolutional neural networks) to detect misplaced inventory or stock discrepancies within the DT. This can reduce inventory errors by up to 25% compared to 5G-based systems, improving order accuracy and customer satisfaction.

Optimized Robotic Navigation and Fleet Coordination. 6G's massive device connectivity and edge computing capabilities allow DTs to coordinate fleets of autonomous mobile robots (AMRs) in real time. A DT can integrate 6G-transmitted data on robot positions, warehouse layouts, and task priorities, while AI (e.g., reinforcement learning) optimizes navigation paths to avoid congestion or obstacles. For instance, in a high-throughput warehouse, if an AMR approaches

a busy picking area, AI can reroute it instantly using 6G's low latency, improving task completion rates.

Seamless Connectivity for Dynamic Operations. 6G's network slicing and AI-driven resource allocation ensure uninterrupted connectivity for mobile workers and robots. For example, a DT can monitor worker movements via 6G-connected wearables or robot positions via onboard sensors. If a worker or robot moves out of an access point's range, AI can predict their trajectory using machine learning models and dynamically reallocate network resources (e.g., shift DT services to a nearby 6G access point). This reduces service disruptions, ensuring continuous operation for critical tasks like real-time inventory updates or order picking.

Implementation Strategies. To deploy 6G-enabled AI-DT frameworks effectively, several strategies can be adopted. Pilot deployments in 6G testbeds, such as those developed by Ericsson or Samsung for industrial IoT, can serve as controlled environments to validate the performance of AI-driven digital twins in real-time inventory tracking and robotic coordination. Network slicing should be utilized to allocate dedicated bandwidth for high-priority tasks like autonomous mobile robot (AMR) navigation, while reserving lower-priority slices for tasks such as reporting, thereby ensuring scalability and efficient resource utilization in large warehouse environments. Lightweight AI models, particularly those based on federated learning, can be optimized for 6G edge nodes to enable real-time analytics without overloading network resources. For instance, adapting Google's federated learning framework could support distributed digital twin updates across edge devices. Additionally, 6G infrastructure must be designed to integrate seamlessly with existing warehouse management systems (WMS) using protocols such as MQTT or OPC UA, ensuring compatibility with legacy IoT setups and facilitating gradual adoption.

Expected Benefits. Integrating 6G technology with AI-driven digital twins offers substantial benefits in warehouse logistics. Real-time DT updates powered by 6G can reduce order fulfillment times by 20%–30%, as demonstrated in early simulations of 6G-enabled logistics systems. The enhanced scalability of 6G, capable of supporting up to ten times more connected devices than 5G, enables large-scale IoT deployments without performance degradation. Furthermore, AI-based optimization of navigation and predictive maintenance can lower operational costs, aligning with benchmarks from automated warehouse deployments. AI-driven connectivity management in 6G environments minimizes communication latency and ensures near-zero downtime, thereby improving throughput, reliability, and the overall efficiency of warehouse operations.

5.5. Big data for predictive analytics in warehouses

The combination of DTs and big data has considerable potential for predictive analytics in warehouse logistics, as it uses enormous IIoT data from sensors and equipment. A key gap is the low scalability of current DT systems to manage the growing volumes of data generated in warehouses, which prevents real-time insights for predictive maintenance and resource optimization [116,117]. Future research should focus on scalable AI-DT architectures that can efficiently handle and evaluate massive amounts of IIoT data. For example, distributed deep learning models might be used with DTs to forecast equipment breakdowns in real time, allowing proactive maintenance scheduling. A crucial challenge is how AI-driven DTs can scale to handle increasing IIoT data volumes for predictive analytics in warehouse logistics.

Data Quality and Noise: Inconsistent or noisy IIoT data can reduce predictive accuracy. Studies should develop AI-driven data cleaning techniques, such as automated outlier detection, to ensure reliable insights. **Energy Efficiency:** High-volume data processing increases energy consumption. Research should investigate energy-efficient algorithms and hardware, such as low-power edge devices, for sustainable operations. **Data Security and Privacy:** Sharing big data across supply chain partners raises security concerns. Future work should explore advanced

encryption methods, such as fully privacy-preserving encryption, to secure DT data while enabling collaborative analytics.

To address the scalability gap and unlock the full potential of big data-driven predictive analytics, AI-integrated digital twin (DT) frameworks must be designed to efficiently process and analyze the massive volumes of Industrial Internet of Things (IIoT) data generated in warehouse logistics. In the following sections, we outline specific applications, implementation strategies, and research directions to enhance predictive maintenance, resource optimization, and operational efficiency, providing actionable insights for practical deployment. Practical Applications of Big Data-AI-DT Frameworks

Proactive Equipment Maintenance. Big data from IIoT sensors (e.g., vibration, temperature, and wear sensors on robotic arms or conveyor systems) can be streamed into a DT to create a real-time model of equipment health. AI, such as distributed recurrent neural networks (RNNs), can analyze these data to predict failures with high accuracy. For example, in an automated warehouse, a DT could detect early signs of bearing failure in a sorting machine, and AI could schedule maintenance during low-demand periods, reducing downtime and maintenance costs, as evidenced by predictive maintenance trials in logistics hubs like DHL.

Real-Time Resource Allocation Optimization. Big data enables DTs to model warehouse operations, including worker movements, robotic tasks, and storage utilization. AI algorithms, such as reinforcement learning, can process IIoT data on order volumes, picking rates, and space constraints to dynamically optimize resource allocation. For instance, in a high-volume retail warehouse, a DT could identify bottlenecks in the picking process, and AI could recommend reassigning workers or robots to specific zones, improving throughput. This approach builds on strategies used by companies like Ocado, which leverage real-time analytics for warehouse efficiency.

Accurate Demand Forecasting for Inventory Management. By integrating IIoT data (e.g., inventory levels, spoilage rates) with external datasets (e.g., market trends, seasonal demand), DTs can enable precise demand forecasting. AI models, such as ensemble methods combining gradient boosting and neural networks, can predict inventory needs with minimal error. For example, in a warehouse handling perishable goods, a DT could use big data to track stock turnover and spoilage, while AI optimizes reorder quantities, reducing waste.

Anomaly Detection for Operational Resilience. Big data-driven DTs can monitor IIoT data streams to detect anomalies, such as unexpected delays or equipment malfunctions. AI algorithms, like isolation forests or autoencoders, can identify irregularities in real time, such as a sudden drop in picking efficiency due to a jammed conveyor. For instance, in a distribution center, a DT could flag an anomaly, and AI could suggest immediate corrective actions (e.g., rerouting tasks), reducing operational disruptions. This enhances resilience and ensures consistent service levels.

Implementation Strategies. To deploy big data-driven digital twin (DT) frameworks effectively, distributed data processing and hybrid architectures should be prioritized. Distributed computing frameworks such as Apache Spark or Flink can handle terabytes of industrial IoT (IIoT) data in real time, enabling DTs to scale efficiently across large warehouse environments by partitioning data between edge and cloud nodes. Implementing edge–cloud hybrid architectures allows low-latency analytics at the edge – such as at sensor gateways – while leveraging cloud platforms for computationally intensive AI model training. For example, AWS IoT Greengrass can be adapted to support real-time data synchronization between physical assets and their digital twins. Additionally, scalable AI models, including federated learning approaches inspired by Google’s framework, enable predictive algorithms to be trained collaboratively across multiple warehouse nodes without centralizing sensitive data, thus enhancing both scalability and privacy. Finally, ensuring compatibility between big data pipelines and existing warehouse management systems (WMS) through standards

like MQTT or REST APIs facilitates smooth integration with legacy infrastructure, promoting gradual and cost-effective adoption.

Expected Benefits. The integration of big data analytics, edge computing, and AI within digital twin frameworks can significantly enhance warehouse operations. Real-time predictive analytics powered by distributed data processing can reduce order processing times by 15%–25%, aligning with benchmarks from data-driven logistics systems. Predictive maintenance and intelligent resource allocation further contribute to a 10%–20% reduction in operational costs, consistent with performance gains observed in automated warehouse deployments. Enhanced demand forecasting minimizes inventory waste by 10%–15%, particularly for perishable goods, thereby improving sustainability and profitability. Moreover, distributed and scalable system architectures enable DTs to process data volumes up to ten times larger than current centralized systems, ensuring long-term scalability and maintaining performance even as warehouse operations expand.

5.6. Quantum computing for advanced optimization

The emerging integration of DTs with quantum computing opens up possibilities for complicated data analysis and safe logistics management [118]. In warehouse settings, quantum-enhanced DTs could improve supply chain security and large-scale inventory simulations, but practical applications are limited. Future study should look at DT-assisted quantum federated learning (DTQFL) for better predictive maintenance and network optimization in warehouses. Additionally, DT-assisted robust quantum key distribution (DARIUS) may improve the security of DT-driven logistical data.

To harness the transformative potential of quantum computing in warehouse logistics, digital twin (DT)-assisted quantum frameworks must be developed to address complex optimization challenges and enhance data security. While current applications are limited due to the nascent state of quantum technology, targeted use cases like DT-assisted quantum federated learning (DTQFL) and DT-assisted robust quantum key distribution (DARIUS) can pave the way for advanced predictive maintenance, network optimization, and secure logistics management. Below, we outline specific applications, implementation strategies, and research directions to bridge the gap between theoretical promise and practical deployment in warehouse operations.

Quantum-Enhanced Predictive Maintenance. Quantum computing’s ability to process vast datasets exponentially faster than classical systems can enhance predictive maintenance within DTs. DTQFL, which combines quantum machine learning with federated learning, can analyze distributed Industrial Internet of Things (IIoT) data (e.g., sensor readings from conveyors or robotic arms) to predict equipment failures with unprecedented accuracy. For example, in a high-throughput warehouse, a DT could model equipment health, and a quantum neural network could identify subtle failure patterns in vibration data, predicting breakdowns earlier than classical models. This reduces downtime, as projected in early quantum computing trials for industrial maintenance.

Large-Scale Inventory and Supply Chain Optimization Quantum algorithms, such as the Quantum Approximate Optimization Algorithm (QAOA), can solve complex combinatorial problems, like optimizing inventory placement or supply chain routing, far more efficiently than classical methods. A DT can simulate warehouse layouts and supply chain networks, while quantum computing optimizes variables like storage allocation or delivery schedules. For instance, in a global distribution center, a quantum-enhanced DT could minimize cross-docking times by solving multi-variable optimization problems, reducing logistics costs and improving order fulfillment speed, based on simulations from quantum logistics research.

Implementation Strategies. To execute quantum-DT frameworks effectively, hybrid quantum–classical architectures should be adopted to leverage the strengths of both computing paradigms. Quantum processors such as IBM’s Qiskit or Google’s Sycamore can be used for complex optimization and simulation tasks, while classical systems handle

DT visualization, control, and data pre-processing. Pilot projects using quantum simulators, such as those offered by Microsoft's Azure Quantum, can serve as experimental testbeds to evaluate frameworks like DTQFL and DARIUS within controlled warehouse environments before deploying full-scale quantum hardware. These pilots enable the validation of performance metrics, scalability, and reliability under realistic operational conditions. Furthermore, integrating quantum-DT systems with existing warehouse management systems (WMS) through APIs or standards like OPC UA ensures compatibility with legacy IIoT infrastructure. Establishing collaborative research ecosystems between quantum computing providers (e.g., D-Wave, IonQ) and logistics firms is also essential to accelerate the development of domain-specific quantum algorithms tailored to warehouse optimization and predictive maintenance.

Expected Benefits. The integration of quantum computing with digital twin frameworks offers transformative potential for warehouse logistics. Quantum-enhanced DTs can improve predictive maintenance accuracy by 20%–30%, leading to a 15%–25% reduction in equipment downtime and maintenance costs. Quantum optimization techniques enable faster and more efficient logistics planning, reducing operational costs by 10%–20% and increasing order fulfillment speed by 15%–20%, as demonstrated in early quantum logistics simulations. Additionally, frameworks like DARIUS strengthen data security through quantum-safe encryption, achieving near-unhackable communication channels and reducing data breach risks by up to 99%—a critical advantage in sensitive supply chain environments. Beyond efficiency and security, quantum computing provides exponential scalability for solving large and complex optimization problems, allowing digital twins to process vast datasets and model highly dynamic warehouse systems with unprecedented precision.

Despite its promise, several challenges must be addressed to fully realize quantum-DT frameworks. Current quantum hardware remains constrained by limited qubit counts and high error rates, requiring continued research into error-corrected quantum systems and hybrid quantum–classical algorithms to bridge the gap until scalable quantum devices become available. The high implementation costs associated with quantum infrastructure also pose barriers to adoption; future research should explore cost-effective models such as cloud-based quantum computing services to democratize access. Algorithm development remains another key challenge, as logistics-specific quantum algorithms – including DTQFL for predictive analytics – are still underexplored. Future studies should prioritize designing and benchmarking domain-specific quantum machine learning models tailored to warehouse optimization and decision-making. Finally, ensuring data privacy in federated quantum learning environments is critical; developing quantum-safe cryptographic protocols and secure data-sharing mechanisms will be essential to protect sensitive logistics data across distributed DT nodes.

6. Conclusion

This review explores the integration of Artificial Intelligence and Digital Twin technologies to optimize warehouse logistics, highlighting current advancements, frameworks, and operational challenges. The convergence of AI methods, including machine learning, deep learning, reinforcement learning, and federated learning, with real-time digital twin simulations enables adaptive warehouse environments capable of dynamic decision-making and continuous process optimization. Key logistics domains such as path planning, multi-robot coordination, system monitoring, and inventory optimization are reshaped by AI-enhanced DT frameworks. Approaches like Q-learning-based AGV routing, GACO hybrid task scheduling, RFID localization, and YOLOv3-enhanced vision systems have improved efficiency, accuracy, and throughput. These innovations reduce travel time, optimize resource allocation, and enhance coordination in complex environments. However, challenges remain, including limited system integration across distributed

networks and insufficient focus on economic factors like ROI and sustainability. The review also highlights the potential of incorporating blockchain, 6G infrastructure, and human–AI collaboration into warehouse optimization. The findings underscore the transformative impact of AI-powered digital twins in revolutionizing logistics and aligning with Industry 4.0 demands.

CRediT authorship contribution statement

Md Mahinur Alam: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Reimbaev Azizbek Nurkat Ugli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis. **Kanita Jerin Tanha:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation. **Taesoo Jun:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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