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AI-IoT Integration in Smart Warehousing: A Systematic Review of Forecasting Technologies and Strategic Applications

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Abstract

This review synthesizes recent advances in combining Artificial Intelligence (AI) and the Internet of Things (IoT) to optimize warehouse operations. Analyzing 18 peer-reviewed studies published between 2021 and 2025, the review identifies four key themes: AI-enhanced inventory forecasting, IoT-driven inventory management, automation and robotics, and digital twin-based strategic planning. Findings show that Machine Learning algorithms significantly improve forecasting accuracy when trained on high-frequency IoT data, while IoT infrastructures, like RFID and sensors, enhance real-time inventory visibility. Robotics enables adaptable, high-throughput operations, and digital twins support predictive modeling and scenario planning. Despite these benefits, challenges remain: many implementations lack real-world validation, and issues such as inconsistent performance metrics, system interoperability, and underrepresented small-scale warehouses limit progress. Additionally, human-machine interaction design is often overlooked. To address these challenges, a four-layer integration model is proposed, covering data acquisition, processing, automation control, and strategic planning, emphasizing the need for a unified sensor infrastructure, learning algorithms, and planning mechanisms. Future research should focus on operational deployment, standardization, and inclusive design to expand applicability across various warehouse sizes. This synthesis provides valuable insights and a conceptual framework for advancing AI-IoT integration in smart warehouses.

Keywords: Warehouse Forecasting, Artificial Intelligence, Internet of Things, Smart Warehousing, Digital Twin Systems

Introduction

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has redefined warehouse operations by enabling real-time inventory monitoring, predictive demand forecasting, intelligent automation, and strategic planning. Recent implementations utilize high-frequency IoT data streams generated from RFID tags, environmental sensors, and connected machinery, and process them through advanced AI techniques, including Machine

Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), to optimize performance and decision-making.

Despite rapid technological advancements, existing literature remains fragmented, often addressing AI, IoT, robotics, and digital twins in isolation or within narrow application scopes. There is a notable lack of cross-thematic synthesis that connects these technologies under a unified strategic framework. Moreover, few studies propose practical taxonomies that map the integration layers between data collection, intelligent processing, automation control, and long-term strategic insight. This review contributes to a structured synthesis of recent advancements in the field. It proposes an integration framework that links AI, IoT, robotics, and digital twin systems in warehousing, thereby bridging technical developments with practical implementation pathways across both operational and strategic layers.

Methodology

This review employed a structured and thematic-driven literature review process, guided by the framework of (Okoli & Schabram, 2010). Instead of a single search session, the review was organized into four separate thematic searches, each focused on a specific technological domain relevant to warehouse forecasting:

1. AI-enhanced inventory forecasting and demand planning
2. IoT-driven inventory management optimization
3. Automation and robotics in smart warehouses
4. Digital twin systems for strategic planning and control

Each thematic stream followed its cycle of identification, screening, eligibility assessment, and inclusion. This multi-session approach ensured depth, relevance, and thematic balance in capturing the state of research from 2021 to 2025.

Phase 1: Thematic Planning and Scope Definition

The review was scoped to include peer-reviewed journal articles and high-impact conference proceedings published in English between January 2021 and April 2025. Only studies published in Q1-Q3 journals indexed by Scimago were considered. Exclusion criteria included editorials, dissertations, non-peer-reviewed sources, and papers that did not explicitly apply AI or IoT technologies in warehouse environments.

Phase 2: Thematic Literature Identification and Screening

Each thematic domain was explored through a dedicated search session, using Boolean operators and domain-specific keywords. The database sources included Scopus, IEEE Xplore, ScienceDirect, and SpringerLink.

- For AI-enhanced forecasting, search terms included “machine learning warehouse”, “AI demand planning”, and “inventory forecasting algorithms.”
- For IoT-driven inventory management, queries included “IoT in warehousing”, “RFID inventory tracking”, and “smart logistics sensors.”
- For automation and robotics, the search focused on “warehouse automation”, “robotic fulfilment systems”, and “AI robotics in logistics.”
- For digital twins, keywords like “digital twin warehouse”, “virtual warehouse modeling”, and “strategic simulation supply chain” were used

Phase 3: Eligibility and Inclusion

Full-text evaluation was conducted independently for each thematic batch. Inclusion required that the study:

- Demonstrate application or evaluation of AI/IoT technologies in real or simulated warehouse settings
- Align clearly with the selected thematic domain
- Provide technical, operational, or strategic insights relevant to warehouse forecasting and control

Eighteen high-quality papers were ultimately included: 5 focused on AI-enhanced forecasting, five on IoT inventory management, four on automation and robotics, and four on digital twins. To reduce bias, the screening and inclusion process for each thematic stream was reviewed independently by two researchers. Discrepancies were resolved via discussion. This dual-review approach enhanced transparency, ensured thematic fit, and reduced selection bias.

Phase 4: Data Extraction and Thematic Synthesis

A structured extraction template was applied to each included paper, capturing metadata such as:

- Publication year and journal
- Geographic context and warehouse type
- Dataset type
- Evaluation metrics and reported outcomes
- Limitations and scalability notes

Synthesis was conducted within and across the four thematic clusters. Patterns, technical gaps, and operational implications were distilled using a qualitative synthesis approach, which informed both the narrative discussion and the proposed integration framework. Figure 1 illustrates the four-stage literature selection process, which involves independent thematic searches, and shows the exclusion criteria and final thematic clusters.

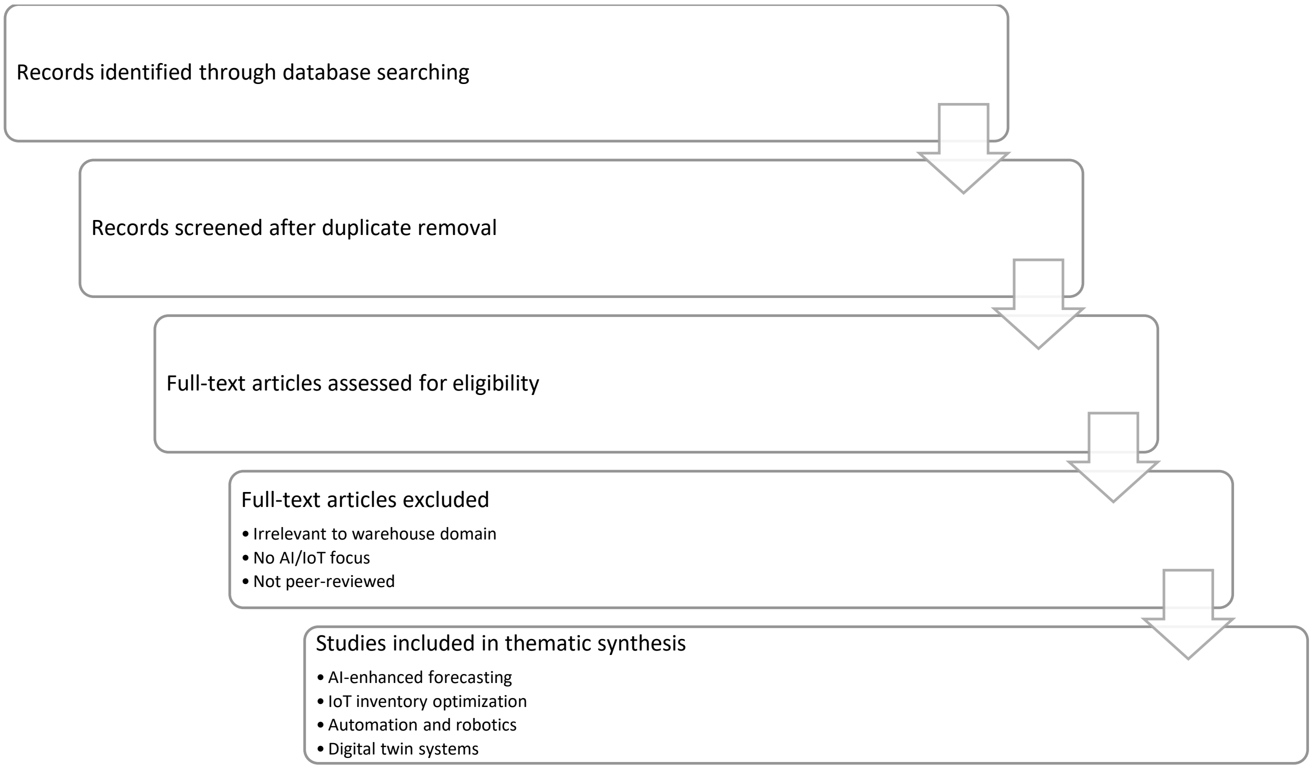

Figure 1 PRISMA-style Article Selection Flow Diagram

AI Forecasting: Supervised vs No-Code Approaches

Across AI-enhanced inventory forecasting studies, a clear contrast emerges between supervised learning techniques and no-code AI implementations. (Albayrak Ünal et al., 2023) classified AI applications by forecasting methods and noted the dominance of supervised algorithms, particularly Neural Networks and Decision Trees, in handling structured warehouse data. These models were frequently trained on granular IoT inputs, such as RFID logs and transaction histories. (Jauhar et al., 2024) demonstrated a low-code approach using AutoML platforms to detect inventory distortions in retail warehouses. Although these platforms reduce technical overhead and promote accessibility, they offer less flexibility in model customization compared to traditional ML setups.

Forecast accuracy and responsiveness further differentiate these studies. While (Aloini et al., 2025) focused on adaptive learning systems that generate short-horizon predictions with real-time IoT streams, (Jarašūnienė et al., 2023) emphasized anomaly detection and stockout prevention through static AI models trained on barcode and GPS-based data. The former enabled dynamic alerts and deviation detection, while the latter prioritized improving inventory cycle times. Notably, all models performed best when paired with high-frequency sensor data, reinforcing the critical role of IoT in driving actionable AI forecasts.

IoT Optimization: Cost-Efficient vs. Technologically Intensive Solutions

In inventory optimization, deployment scale and cost constraints shape the implementation of IoT strategies. For example, (Maheshwari et al., 2021) and (Ruiz et al., 2024) targeted small-scale operations like Micro, Small, and Medium Enterprises (MSMEs) by employing lightweight RFID and temperature sensors alongside rule-based controls. These models improved inventory shelf life and accuracy without extensive infrastructure investment. On the other end, (Kotru & Batra, 2024) integrated Wireless Sensor Networks (WSNs) and advanced ML models like decision trees, ensembles, and regression techniques to optimize warehouse resource allocations, achieving high accuracy at 93.75% but at higher computational costs.

Real-time monitoring also varies in complexity. (Winardi et al., 2024) proposed a dashboard-integrated IoT system for tracking stock availability and issuing alerts, while (Villegas-Ch et al., 2024) deployed a hybrid computer vision-IoT system to detect shelf occupancy and item misplacement. The former is cost-effective and suitable for real-time visibility, whereas the latter offers enhanced automation but requires sophisticated edge processing. Collectively, these studies demonstrate that IoT inventory systems operate along a spectrum, ranging from basic rule-based visibility to intelligent, predictive infrastructure. Aligning technological sophistication with warehouse scale is essential for scalable implementation.

Automation and Robotics: Fixed Systems vs Adaptive Intelligence

Warehouse automation strategies span a spectrum, from fixed-function systems to adaptive cyber-physical ecosystems. (Kembro & Norrman, 2022) showed how Swedish retailers have adopted Automated Storage and Retrieval Systems (AS/RS) and robotic shuttles to handle outbound tasks efficiently, often customizing automation types to fit product assortment and order volumes. These systems improve throughput but lack adaptability. In contrast, (van Geest et al., 2021) proposed a modular reference architecture that supports reconfigurable robotic deployments via standardized communication and human-robot task allocation protocols.

Advanced AI capabilities further differentiate system intelligence. (Baouya et al., 2024) introduced the BRAIN-IoT framework, which uses semantic assurance and runtime monitoring to coordinate heterogeneous warehouse robots safely. Meanwhile, (Tang et al., 2023) explored AI-driven object recognition paired with Mixed Reality (MR) for intuitive robot control, enabling human operators to interact with robots in dynamic environments without relying solely on pre-coded instructions. From a systems perspective, (Youssef et al., 2022) mapped automation maturity levels within Industry 4.0 paradigms, identifying cyber-physical integration and predictive maintenance as future trajectories. These studies collectively suggest a shift: early automation focused on replacing labor, whereas modern systems emphasized intelligent adaptation and real-time coordination within connected ecosystems.

Digital Twins and Strategic Insights

Digital Twin (DT) systems in warehousing forecasting demonstrate two main application paths: operational control and strategic planning. (Ho et al., 2025) deployed a Deep Reinforcement Learning (DRL) enhanced digital twin framework to manage robot navigation under 5G-enabled ultra-reliable low-latency communication (URLLC) conditions. Their hybrid edge-cloud system dynamically allocates computational tasks, achieving energy-efficient control and low-latency responsiveness. In comparison, (Wu et al., 2022) implemented a DT system for tracking mobile warehouse trolleys using RFID and real-time location systems (RTLS) sensors. The systems enabled fine-grained, real-time traceability but were primarily focused on optimizing assets at the individual level.

Strategic frameworks, such as that of (Maheshwari et al., 2023), proposed a taxonomy of DT capability levels, from monitoring to autonomous decision execution. The model spans real-time visualization, diagnostics, predictive analytics, and prescriptive planning. Similarly, (Barata & Kayser, 2024) positioned DTs as key enablers of Industry 5.0, highlighting human-machine co-creation, ethical automation, and distributed cognition. This broader view shifts DTs from operational enablers to strategic assets with contextual intelligence. Operational implementations are still emerging. For instance, (Hu et al., 2023) designed a stereo-warehouse DT for cold-chain logistics, integrating 3D environmental models and edge sensors to ensure temperature control. Although still in prototype stages, this study demonstrates the potential of DTs for domain-specific decision support, particularly in perishable logistics.

Together, these studies emphasize that digital twins provide both tactical control and strategic foresight. When embedded within AI-IoT infrastructures, DTs act as the orchestrating layer, synchronizing data flow, predictive learning, and real-time simulation for warehouse-wide optimization.

Table 1
Synthesis Matrix of AI and IoT Applications in Warehouse Forecasting

Author(s)	Contribution	AI/IoT Method	Application Context	Key Outcome
Maheshwari et al. (2021)	Low-cost IoT inventory tracking	RFID, rule-based logic	MSMEs, perishable goods	Cost-efficient visibility and shelf-life optimization
van Geest et al. (2021)	Modular automation architecture	Reconfigurable robotic protocols	Industry 4.0 smart warehouse	Flexible task allocation, scalability
Kembro & Norrman (2022)	Adoption of AS/RS systems	Fixed robotic systems	Swedish retailer	Increased outbound efficiency
Youssef et al. (2022)	Maturity mapping of warehouse automation	Industry 4.0 architecture	Global warehouse systems	Future trajectory toward cyber-physical integration
Wu et al. (2022)	Asset-level DT tracking	RFID + RTLS	Finished goods logistics	Real-time traceability
Albayrak et al. (2023)	Classify AI forecasting models	Neural networks, decision trees	Retail inventory forecasting	Improved short-term demand accuracy
Hu et al. (2023)	Cold-chain warehouse twin	3D environment + edge sensors	Perishable logistics	Prototype for temperature control and planning

Jarašūnienė et al. (2023)	Stockout risk identification	Static AI models, GPS/barcode	Logistics warehouses	Reduced inventory cycle time
Jauhar et al. (2024)	No-code AI for anomaly detection	AutoML, inventory distortion detection	Retail warehouses	Increased accessibility with moderate forecasting accuracy
Tang et al. (2023)	Mixed Reality for robot interaction	AI + MR object recognition	Human-robot collaboration	Intuitive control with adaptive navigation
Maheshwari et al. (2023)	DT capability taxonomy	Monitoring to autonomous planning	Strategic warehouse planning	Defined levels of DT maturity
Baouya et al. (2024)	Functional assurance for robots	Semantic AI, BRAIN-IoT	Robot coordination	Safe, runtime-monitored robot operations
Barata & Kayser (2024)	DTs in Industry 5.0	Human-machine ethics, co-creation	Strategic foresight	Shift toward contextual intelligence
Kotru & Batra (2024)	IoT resource allocation optimization	WSN + ML ensemble models	Medium-scale warehouses	93.75% accuracy in stock-level predictions
Ruiz et al. (2024)	Affordable smart warehouse design	RFID, temperature sensors	Small-scale warehouses	Improved accuracy without high infrastructure cost
Villegas-Ch et al. (2024)	Item tracking via vision and ML	Computer vision + IoT	Retail shelves	Accurate misplacement detection
Winardi et al. (2024)	Real-time stock dashboard	Sensor network, alert system	Small warehouse operations	Enhanced monitoring with minimal overhead
Aloini et al. (2025)	Adaptive AI alerting	Real-time ML, IoT streams	Cycle time prediction	Real-time alerts, improved responsiveness
Ho et al. (2025)	DRL-based digital twin control	Deep RL, hybrid edge-cloud	5G robot navigation	Low-latency, energy-efficient control

Conceptual Framework: AI-IoT Integration in Smart Warehousing

Before proposing the conceptual integration framework, it is essential to understand how smart warehouse technologies have evolved. The development has progressed from isolated sensor-based tracking systems to advanced AI-driven automation and digital twin environments. Recognizing this trajectory provides the necessary context for the layered model proposed in this paper. Table 2 presents a timeline illustrating the six key stages in the evolution of warehouse technologies, highlighting how each phase contributes to the growing integration of AI, IoT, and DT systems.

Table 2
Evolution of Smart Warehouse Technologies

Timeframe	Stage	Technology Focus	Key Features
Early 2010s	Sensor-Based IoT	Basic IoT (RFID, barcode, GPS)	Real-time tracking, environment monitoring, and static rule-based alerts
Mid 2010s	IoT + Dashboards	IoT with centralized monitoring dashboards	Data visualization, manual decision-making support
Late 2010s–2020	AI-Augmented IoT	ML/DL for inventory forecasting and anomalies	Automated predictions, stockout detection, IoT-trained models
2020–2022	Robotics + AI	Robotics integrated with AI decisions	Automated retrieval, AGVs, robotic task execution based on AI outcomes
2022–2023	Digital Twin Systems	Digital replicas with real-time data sync	Simulation, diagnostics, predictive analytics, planning
2024+ (emerging)	Full AI-IoT-DT Integration	Multi-layer orchestration (Data → AI → Actuation → DT)	Real-time optimization, human-machine co-creation, adaptive decision support

To consolidate insights from the four thematic domains reviewed — AI forecasting, IoT-driven inventory management, automation and robotics, and digital twin-based strategic planning — this paper proposes a layered integration model titled the AI-IoT Integration Framework for Smart Warehousing. This framework consists of four interdependent layers, each representing a core functional component in the intelligent warehousing pipeline.

Data Layer

This foundational layer comprises IoT-enabled data acquisition technologies. Devices such as RFID readers, GPS trackers, temperature and humidity sensors, and motion detectors continuously collect real-time data on warehouse conditions, inventory location, and environmental parameters. This layer ensures granularity, frequency, and contextual relevance necessary for downstream intelligence.

AI Processing Layer

Data generated from the sensor ecosystem is processed in this layer using Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) algorithms. These models handle various tasks, including inventory forecasting, demand prediction, anomaly detection, and classification of warehouse conditions. The algorithms may operate on edge nodes or cloud systems, depending on latency and computational requirements. Outputs from this layer include forecasted trends, optimized inventory thresholds, and early warnings for operational anomalies.

Actuation Layer

This layer represents the execution of AI decisions through robotic systems, Wireless Sensor Networks (WSNs), and Cyber-Physical Systems (CPS). Automated Storage and Retrieval Systems (AS/RS), collaborative robots, and smart conveyor mechanisms operate based on AI-generated outputs, making physical adjustments to inventory handling, restocking, and rerouting. Feedback from this layer can be reintegrated into the AI models for adaptive learning and improvement.

Strategic Insight Layer

At the highest level, Digital Twin (DT) systems simulate the entire warehouse environment to provide diagnostics, predictive analytics, and prescriptive planning. These virtual representations utilize real-time and historical data to forecast scenarios, monitor system health, and inform strategic decisions, such as resource reallocation, warehouse layout redesign, or seasonal stocking strategies. This layer bridges operational control with long-term decision support, aligning with the objectives of Industry 4.0 and 5.0.

By aligning studies within this conceptual structure, the framework provides a cohesive view of how AI and IoT technologies interact across operational and strategic dimensions in smart warehousing. Each of the thematic sections in this review maps to at least one of these layers, reinforcing the interconnected nature of AI-IoT systems.

Figure 2 shows the layered model that outlines how IoT-driven data acquisition, AI-based processing, actuation mechanisms, and strategic digital twin systems interact to support intelligent, adaptive, and scalable warehouse operations.

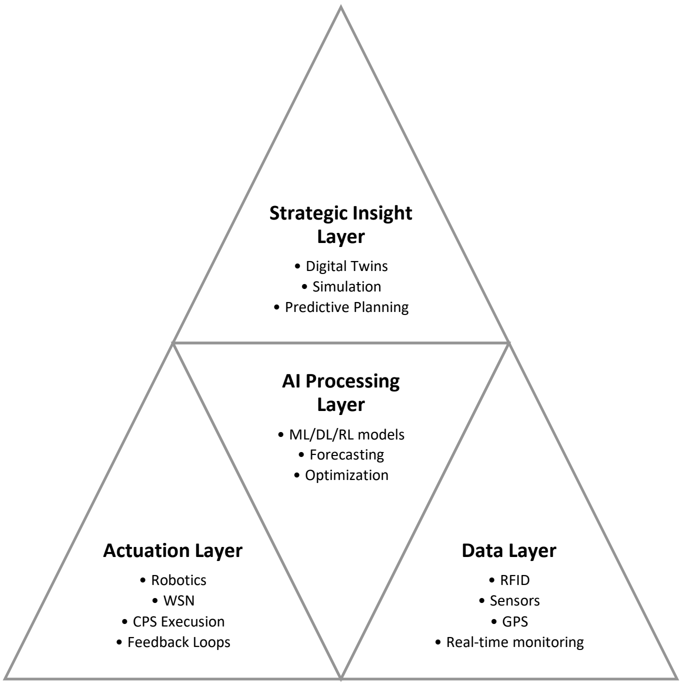

Figure 2 Proposed AI-IOT Integration Framework for Smart Warehousing

Discussion and Limitations

The integration of AI and IoT in warehouse forecasting is advancing rapidly, yet progress remains uneven across system layers. While many studies show maturity in AI forecasting (Layer 2) and automation systems (Layer 3), foundational elements such as sensor infrastructure (Layer 1) and strategic integration via digital twins (Layer 4) are less developed. This imbalance limits the effectiveness of even the most advanced models, especially when deployed in real-world environments with incomplete or low-resolution data. Digital twin systems, while conceptually rich, remain largely in experimental phases. The potential for scenario planning and strategic insight is clear, yet practical implementation often lacks full operational coupling with real-time AI and robotic systems. Additionally, most reviewed frameworks are designed for well-resourced environments, offering limited guidance for adoption in small and medium-sized enterprises (SMEs), which face constraints in infrastructure, budget, and technical expertise.

Several recurring limitations were identified. First, many studies rely on simulations or isolated testbeds, which limit their generalizability. Second, performance metrics are inconsistent across themes, ranging from accuracy score to latency or energy usage, hindering comparative evaluation. Third, integration complexity is often underestimated, with minimal discussion on issues such as data heterogeneity, legacy system compatibility, or real-time synchronization. Importantly, human-centric design and ethical considerations are noticeably underexplored. Very few studies address how warehouse staff interact with AI systems, interpret outputs, or adapt to changing automation roles. Without greater attention to usability, transparency, and inclusion, deployment risks becoming technically feasible but operationally fragile.

To support sustainable and scalable adoption, future research should focus on cross-layer interoperability, standardized evaluation metrics, SME-specific deployment models, and integration of human factors into AI-IoT design frameworks.

Conclusion and Future Works

This review consolidated recent advancements in the integration of AI and IoT within the warehousing domain, structured across four thematic areas: AI-enhanced inventory forecasting, IoT-driven inventory management, automation and robotics, and digital twin-based strategic planning. Drawing on 18 peer-reviewed studies from 2021 to 2025, the review confirmed that the convergence of AI and IoT technologies yields significant improvements in forecasting accuracy, inventory visibility, operational agility, and long-term planning. To unify these advancements, the paper proposes a four-layer conceptual model comprising the Data Layer, AI Processing Layer, Actuation Layer, and Strategic Insight Layer, which articulates the interaction between sensor infrastructure, intelligent algorithms, robotic systems, and digital twins. This layered framework highlights the interconnected nature of intelligent warehouse systems, offering a practical lens for both researchers and industry practitioners to align technological investments with strategic warehousing goals.

Despite substantial progress, several gaps in research and implementation remain. Most existing studies are limited to controlled environments or simulation settings, with limited insights into long-term deployment, human interaction, and system benchmarking. To address these gaps, three key directions are recommended for future work:

1. Future research should focus on evaluating AI-IoT frameworks over extended periods and in real-world warehouse settings to assess stability, adaptability, and return on investment under operational variability.
2. There is a critical need to investigate how warehouse personnel interact with AI-driven systems, interpret predictions, and adjust behaviors. This includes exploring intuitive dashboards, explainable AI (XAI) interfaces, and inclusive design principles that reduce training overhead and cognitive load.
3. The field lacks standardized benchmarks for evaluating the performance, cost efficiency, and scalability of AI-IoT systems. Future studies should propose comprehensive metrics that include not only accuracy and latency but also usability, energy efficiency, and interoperability.

This review provides a foundation for both academic inquiry and industrial development of AI-IoT convergence models in smart warehousing. By synthesizing fragmented developments into a unified conceptual model and identifying actionable research directions, the paper supports the transition from experimental prototypes to scalable, context-aware, and human-centered smart warehouse systems.

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