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Design and Implementation of a Semi-automated Warehouse System for Smart Logistics in Urban Infrastructure

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In this paper, we present the design and implementation of a semi-automated warehouse system tailored for urban smart logistics. By integrating IoT-enabled sensor networks for localization, identification, and real-time monitoring, AI-based control modules, and cloud platforms, the system aims to enhance operational throughput and reduce manual interventions. To evaluate cost performance and inform optimization strategies, an activity-based costing (ABC) model was applied to analyze unit costs across product handling groups. Furthermore, multi-period simulations over a four-week span were conducted to assess predicted versus actual performance, supporting dynamic decision-making in logistics resource planning. The results highlight measurable improvements in cost efficiency, model accuracy, and profit optimization. Visual analytics and comparative ABC evaluation demonstrate the system's scalability and practical value in smart city environments. This work illustrates a concrete application of IoT-based sensor technologies in warehousing, bridging the gap between theoretical sensor research and practical deployment in smart city logistics. Future directions include full automation, integration with reinforcement learning for adaptive control, and the deployment of digital twins for real-time logistics optimization.

1. Introduction

The rise of global urbanization, coupled with the exponential growth of e-commerce, has introduced unprecedented challenges to traditional logistics and warehousing systems. In densely populated cities, the demand for fast, accurate, and cost-efficient distribution has escalated, putting immense pressure on existing supply chain infrastructures. Conventional warehouse operations, often reliant on manual labor and fragmented management systems, struggle to meet the expectations of modern logistics in terms of speed, scalability, and accuracy.[(1)] To address these concerns, the integration of AI and IoT – collectively referred to as AIoT – has emerged as a transformative approach to modernizing logistics infrastructure. AIoT

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technologies enable real-time sensing, data analytics, predictive modeling, and system optimization, which are essential for streamlining warehouse operations and improving operational efficiency.[2]

In this study, we focused on the design and implementation of a semi-automated warehouse system tailored for urban logistics environments.[3] Unlike fully automated solutions, which often require substantial capital investment and infrastructure overhaul, semi-automated systems offer a more flexible and scalable alternative that combines human supervision with intelligent automation. The proposed system includes AI-assisted trolley-picking workflows, intelligent shelving systems with visual indicators, and computer vision modules for inventory scanning and label recognition. In addition to its architectural and technical features, in this research, we adopted an ABC approach to assess the economic viability of the semi-automated system.[4] By analyzing cost drivers related to warehouse operations, such as labor intensity, equipment utilization, and energy consumption, we aim to provide a data-driven basis for evaluating different product handling strategies and optimizing warehouse configurations. Through pilot deployment in a medium-sized urban logistics hub, the system demonstrates its potential to reduce operational delays, enhance inventory accuracy, and provide actionable insights for logistics decision-makers. The outcomes of this research contribute to the broader discourse on smart urban infrastructure, emphasizing the value of semi-automated solutions in achieving sustainable, efficient, and intelligent city logistics.

2. Literature Review

The transformation of warehousing and logistics systems under the influence of Industry 4.0 has attracted considerable attention in both academic and industrial domains. Smart warehousing, a key component of smart logistics, integrates automation technologies, sensor networks, and AI to enhance operational efficiency, transparency, and decision-making in supply chain processes.[5] Smart warehousing involves the application of technologies such as automated storage and retrieval systems, autonomous mobile robots (AMRs), radio frequency identification (RFID), and warehouse management systems (WMS).[6] These technologies collectively aim to reduce labor costs, improve order accuracy, and optimize space utilization. However, many small- and medium-sized enterprises (SMEs) are hesitant to adopt fully automated solutions owing to the high upfront investment and system complexity. Semi-automated systems, which combine human operators with AI-guided assistance, offer a promising compromise. These systems typically retain manual picking or supervision but enhance decision-making through intelligent support, such as real-time path recommendations, load balancing, and visual alerts for optimal item placement.

As emphasized in recent literature, IoT-based sensor applications provide the foundation for these semi-automated systems by enabling real-time monitoring and precise localization. Examples include wearable inertial measurement units (IMUs) for worker motion tracking, RFID and barcode readers for product identification, and ultra-wideband (UWB) modules for indoor localization.[7] In addition, computer vision sensors have been applied to object recognition, shelf inspection, and worker–robot interaction, extending the practical value of sensor networks in warehouse environments. Compared with earlier studies focusing solely on automation hardware, current approaches highlight the synergy between IoT sensors and AI algorithms in creating adaptive, human-centered systems.

AIoT, the convergence of AI algorithms with IoT infrastructure, plays a crucial role in enabling data-driven logistics. IoT sensors gather real-time data from various sources (e.g., shelf weight, temperature, and barcode readers), which are then processed by AI models to detect anomalies, predict demand, and optimize the warehouse layout.(8) Recent studies emphasize the role of AIoT in predictive maintenance, energy management, and adaptive resource allocation within smart warehouses.(9) The use of computer vision for object recognition, gesture control, and automated inspection has also advanced significantly, enabling intuitive interaction with semi-autonomous systems. Traditional cost accounting methods often fail to accurately allocate overhead in complex logistics operations. ABC, in contrast, assigns costs on the basis of actual activities and resource consumption, allowing a more precise analysis of cost drivers in warehouse operations.(10) ABC has been applied to evaluate picking processes, storage density, product handling frequency, and error correction costs in warehouse environments. By incorporating ABC into smart warehouse design, researchers can compare different system configurations, measure the economic impact of automation levels, and identify optimal product combinations to maximize throughput and profitability.

Despite these advancements, comparative analyses between semi-automated warehouse studies remain limited. Some researchers have explored RFID-enabled picking accuracy or AMR-based order consolidation,(11) yet very few works combine IoT-enabled sensor networks with ABC modeling to evaluate both operational efficiency and cost performance. Our study differs from prior research by emphasizing a multi-parameter evaluation pickup time, error reduction, and unit cost within an urban logistics context, thus offering a broader perspective on system scalability and economic feasibility.

With this study, we seek to fill these gaps by designing and implementing a semi-automated warehouse prototype that integrates IoT-based sensor technologies with ABC modeling, tested within an urban logistics context.

3. System Architecture

The semi-automated warehouse system proposed in this study is designed to support intelligent logistics operations in dense urban environments. The system integrates human operators with AI-assisted tools and IoT-based sensing technologies, forming a hybrid architecture that optimizes inventory flow, reduces human error, and supports flexible deployment without the need for full automation infrastructure.

3.1 AI-assisted trolley picking system and workflow integration

Figure 1 illustrates the core function of the AI-assisted trolley picking system within the smart warehouse. In this setup, a human worker maneuvers a cart equipped with embedded sensors and AI computation units. The system integrates wearable IMUs on the worker for

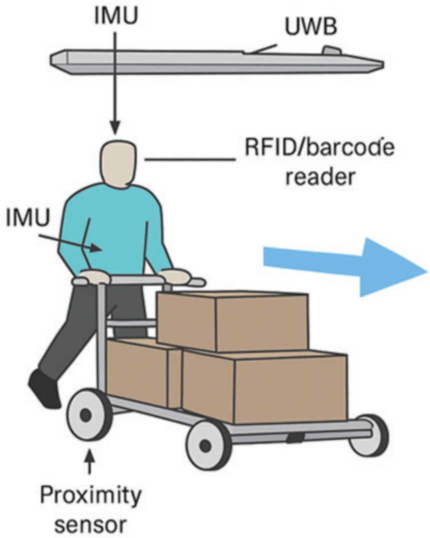

Fig. 1. (Color online) AI-assisted trolley picking system.

motion tracking, RFID/barcode readers on the trolley for product identification, and UWB tags for precise indoor localization. Computer vision is used to recognize products and their placements, whereas weight sensors on the cart ensure proper load balancing and verification. Overhead rails are equipped with smart indicators and UWB anchors for localization, together with environmental sensors that enhance spatial awareness. These sensing components allow the system to monitor positional data and provide navigation cues visually or through voice guidance to streamline the picking path.

This modular architecture supports dynamic inventory assignment and ensures synchronized data flow with cloud analytics dashboards through edge AI gateways, forming the backbone of intelligent warehouse operations. Workers are equipped with either tablet terminals or AR glasses connected to the AIoT network, receiving real-time picking instructions from the system's AI module. On the basis of real-time inventory levels and delivery orders, the system dynamically optimizes picking paths. Smart shelves illuminate the correct item location, whereas load sensors and RFID checkpoints verify product retrieval.

Figure 2 shows a visual representation of the shelf unit configuration with integrated load sensors and visual cues, supporting real-time item location feedback. As shown in Fig. 2, the intelligent warehouse storage system is composed of multi-tiered smart shelving units equipped with embedded LED indicators and load sensors for weight monitoring, RFID readers for identification, and environmental sensors (e.g., temperature and humidity) for product preservation. These shelves are designed not only for physical storage but also for real-time interaction with the AIoT network.

The indicator lights on each shelf communicate dynamic inventory status such as item presence, availability, or misplacement, providing immediate visual feedback to workers or autonomous systems. Additionally, the overhead surveillance structure integrates ceiling-mounted cameras for object recognition and UWB anchors for continuous indoor locatization. Together, these components enable real-time spatial monitoring and object tracking, thereby

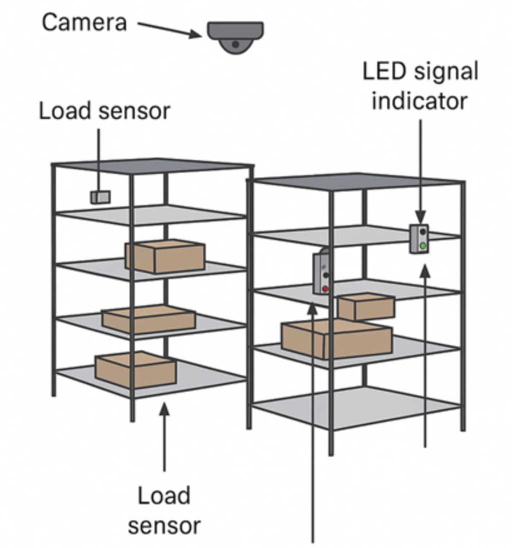

Fig. 2. (Color online) Intelligent warehouse storage system.

enhancing both safety and operational accuracy. This architecture allows the system to optimize space utilization, support predictive stocking, and ensure efficient item retrieval, forming a critical component of the automated warehouse infrastructure.

3.2 Real-time label verification

Product labels are scanned using an overhead camera module. The images are processed using a lightweight optical character recognition (OCR) engine running on an edge device, which identifies stock keeping unit (SKU) numbers, expiry dates, and quantity confirmation. Figure 3 depicts the interface of the label verification system, highlighting detection accuracy and integration with the warehouse's WMS. However, Fig. 3 illustrates the integration of computer vision and OCR in the warehouse environment. A camera module is shown scanning product labels on packages, which are then interpreted in real time and cross-referenced with the warehouse management database. This process ensures the immediate verification of item identity, quantity, and placement accuracy. Visual confirmation is also provided on a nearby screen for operator double-checking or manual override when necessary. The AI-based recognition system significantly reduces human error in item identification and facilitates seamless coordination between inbound and outbound logistics. Furthermore, the setup supports automated updates to inventory records, enhancing operational transparency and traceability throughout the supply chain.

3.3 White-box + black-box architecture

Figure 4 shows the system architecture and decision flow within the AIoT-based smart warehouse. The interaction begins with physical data acquisition through sensors, cameras, and

Fig. 3. (Color online) Label recognition interface.

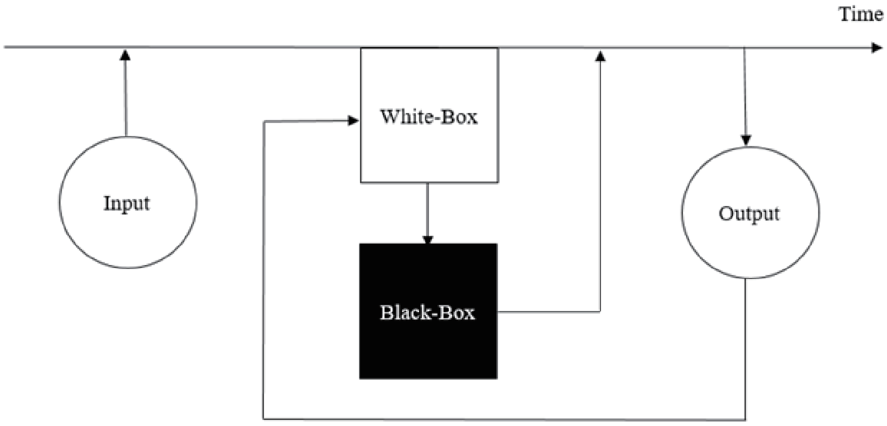

Fig. 4. White-box and black-box integration flowchart.

smart indicators embedded in trolleys and shelving units. The input data is processed at the edge gateway, which hosts lightweight AI models for low-latency inference such as route suggestions, load validation, or anomaly detection. Simultaneously, more complex analyses involving demand forecasting, replenishment planning, and efficiency optimization are handled by cloud-based AI modules. The system leverages both "white-box" models transparent logic such as rule-based or explainable AI and "black-box" models such as deep learning networks to support robust decision-making. Outputs include visual or audio instructions to human operators, lighting signals on smart shelves, and automated updates to the warehouse dashboard. This interactive feedback loop enables real-time coordination between human workers and AI agents, forming a hybrid intelligence system that dynamically adapts to operational needs while maintaining accuracy, speed, and traceability.

3.4 Hardware and IoT infrastructure

Each shelf unit includes (a) RFID tags and barcode readers, (b) load-cell weight sensors, (c) LED guidance indicators, and (d) an edge computing module (NVIDIA Jetson Nano or equivalent). The entire system communicates over a mesh network using the Message Queuing Telemetry Transport protocol, with real-time dashboards built on cloud platforms such as Amazon Web Services, Azure IoT Hub, or Google Cloud Platform. In this section, we present a comprehensive overview of the smart warehouse system enabled by AIoT technologies. From the AI-assisted trolley picking process to intelligent shelving and product recognition, each subsystem demonstrates how hardware, software, and cloud infrastructure are tightly integrated to support real-time logistics operations. The use of edge computing enables responsive local control, whereas cloud synchronization ensures centralized analytics and scalability. Figure 4 encapsulates the interaction flow among all components, highlighting the collaboration between human operators, sensor inputs, and AI-driven decision modules. The hybrid use of transparent and opaque AI models provides both reliability and interpretability. Together, these elements form a robust smart warehouse framework capable of adapting to dynamic inventory demands, improving operational throughput, and laying the groundwork for future automation enhancements. In the following section, a comparative analysis will examine how such AIoT-based systems differ from traditional warehouse and logistics environments in terms of efficiency, scalability, and sustainability.

4. Functional Modules and ABC Cost Model

To assess the operational efficiency and financial feasibility of the proposed semi-automated warehouse system, in this section, we describe the key system functions and introduce an ABC model. The goal is to quantify cost drivers, identify high-efficiency configurations, and simulate the profitability of product handling combinations within the warehouse.[10]

4.1 Functional modules

The semi-automated AIoT-based warehouse system is composed of three core modules that work in concert to enhance operational efficiency, accuracy, and visibility. The smart shelf module integrates embedded load sensors, LED indicators, and position tracking technologies to support multiple critical functions. It continuously monitors inventory weight and item presence, ensuring accurate stock levels. During order fulfillment, the system provides visual guidance through LED cues to direct operators to the correct item locations. Additionally, it can detect errors or incomplete retrievals in real time, helping to minimize picking inaccuracies and enabling prompt corrective action. The AI-assisted trolley module plays a complementary role by supporting operators throughout the picking process. Equipped with edge AI capabilities and image recognition, the trolley displays dynamic picking sequences tailored to the task at hand. It also verifies item collection through label scanning and OCR, ensuring that each selected item matches the order requirements. Furthermore, the trolley offers immediate feedback to the operator, which helps prevent errors and maintain efficiency in workflow. At the system's core is the central coordination dashboard, a cloud-based interface that aggregates data from all IoT-enabled components. This dashboard visualizes key performance indicators such as average pick time, shelf utilization, and error rates, providing managers with a real-time overview of operational performance. It also supports proactive decision-making by enabling resource adjustments, task reallocation, and strategy optimization based on live system insights. Together, these modules form a cohesive and intelligent system that streamlines warehouse operations, enhances picking accuracy, and provides actionable data for continuous improvement.

4.2 Activity-based cost model

ABC analysis assigns overhead and operational costs to specific warehouse activities based on their actual resource consumption. In this model, we define the following activities and associated cost drivers in Table 1:

The total operational cost per product unit is expressed as

$$C = c_1 T_p + c_2 E + c_3 A_{ai} + c_4 I_{ocr} + c_5 L_{led}\,, \tag{1}$$

where c_1–c_5 are cost rates (e.g., TWD/min and TWD/kWh), and all variables are measurable through the IoT infrastructure.

4.3 Product combination analysis

Suppose we analyze two product groups.

(a) Group A: 20 items, light weight, high retrieval frequency

(b) Group B: 10 items, heavy weight, low retrieval frequency

Assuming:

T_p: Group A = 0.7 min, Group B = 1.2 min

E: Both = 0.02 kWh/item

A_{ai}: Group A = 3 tasks/item, Group B = 1 task/item

I_{ocr}: Group A = 2 images/item, Group B = 1 image/item

L_{led}: Group A = 3 times/item, Group B = 2 times/item

Cost coefficients: $c_1 = 2.5$, $c_2 = 4.5$, $c_3 = 0.8$, $c_4 = 0.6$, $c_5 = 0.2$

4.4 Sample cost calculation

(a) Group A: Cost_A = 2.5(0.7) + 4.5(0.02) + 0.8(3) + 0.6(2) + 0.2(3) = 1.75 + 0.09 + 2.4 + 1.2 + 0.6 = 6.04 TWD

(b) Group B: Cost_B = 2.5(1.2) + 4.5(0.02) + 0.8(1) + 0.6(1) + 0.2(2) = 3.0 + 0.09 + 0.8 + 0.6 + 0.4 = 4.89 TWD

Table 1
Activity-based cost drivers and corresponding units.

Activity	Cost driver	Unit	Symbol
Picking and sorting	Time per pick	min/pick	T_p
System power consumption	kWh per operation	kWh/h	E
AI computation overhead	Inference tasks	tasks/h	A_{ai}
Label recognition processing	Images processed	images/h	I_{ocr}
Shelf guidance use	LED triggers per operation	count	L_{led}

As shown in Fig. 5, although Group A has a higher frequency and a lower handling time, its AI-assisted support complexity increases the per-unit cost. This reveals a trade-off between frequency and system utilization cost, guiding managers to optimize the SKU layout and AI processing distribution.

5. Pilot Deployment and Results

To evaluate the performance, feasibility, and cost-effectiveness of the proposed semi-automated warehouse system, a pilot deployment was carried out at a logistics hub located in a mixed-use urban district. The site handles small-to-medium-scale distribution operations for e-commerce and retail clients.

5.1 Deployment setup

The experimental setup was designed to simulate a semi-automated warehouse environment incorporating AIoT-based modules. The virtual testbed consisted of two distinct product-handling workflows: Group A simulated a traditional manual picking process, whereas Group B represented a semi-automated configuration with AI-assisted operations. The modeled warehouse included four virtual aisles of smart shelves equipped with simulated LED indicators, OCR-enabled vision systems for label recognition, and Jetson Nano-based edge computing units assigned per aisle. These edge modules performed real-time inference and decision-making to guide workers via visual prompts. A cloud-based dashboard collected and visualized system data, including energy usage, task completion rates, and error frequencies. To simulate the operational cost structure, an ABC framework was implemented, tracking unit costs derived from specific resource-consuming actions such as inference cycles, LED activation, and power consumption. Both groups were tested across identical virtual conditions for four operational weeks. The setup enabled a controlled environment to compare cost-effectiveness, accuracy, and process efficiency between conventional and AIoT-augmented workflows, the results of which are presented in Fig. 5.

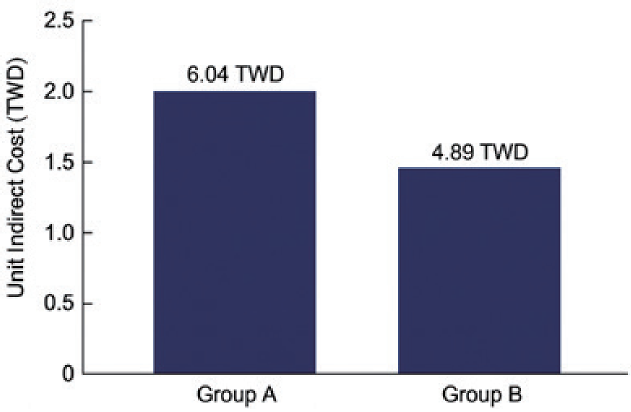

Fig. 5. (Color online) System deployment layout in pilot warehouse.

This bar chart illustrates a comparison of unit indirect costs between two operational configurations in the warehouse system. Group A represents the baseline process without intelligent automation, whereas Group B incorporates AIoT-based enhancements such as vision-guided picking and edge AI decision-making. The vertical axis shows the unit indirect cost in New Taiwan Dollars (TWD), highlighting a notable cost reduction from 6.04 TWD in Group A to 4.89 TWD in Group B. The cost components include energy consumption, AI inference loads, LED trigger events, and label recognition tasks, as calculated using an ABC model. The significant decrease in unit indirect cost reflects the efficiency gains and process optimization achieved through the deployment of smart technologies.

The warehouse measures 25.0 × 18.0 m^2 and is organized into three rows of shelving racks with aisles of 2.5–3.0 m for worker and trolley movements shown in Fig. 6. A designated pickup/drop-off station is located at the right side of the warehouse. Overhead sensors (UWB anchors and cameras) are installed at the corners for localization and monitoring. Each shelf unit is equipped with load sensors and LED indicators to support real-time item detection and visual guidance.

5.2 Operational metrics collected

The deployment of the proposed semi-automated warehouse system was carried out over a four-week operational period, during which key performance indicators (KPIs) were systematically monitored to evaluate its effectiveness. As summarized in Table 2, a comparative analysis between the traditional manual picking process and the semi-automated approach reveals substantial improvements across operational efficiency, spatial utilization, human

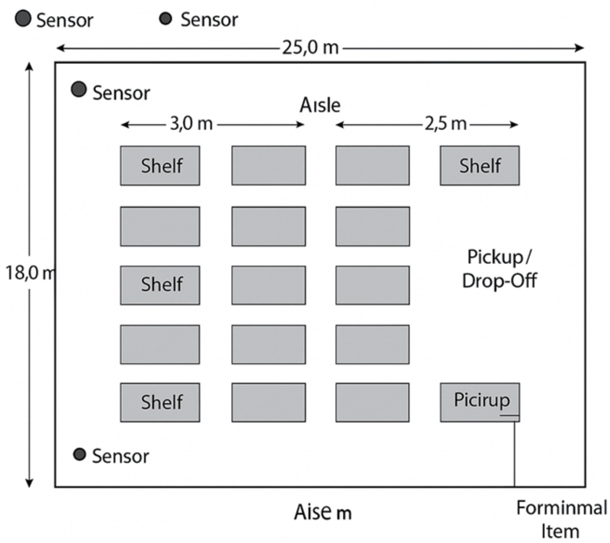

Fig. 6. (Color online) Schematic floor layout of the experimental warehouse with dimensions.

Table 2
Comparative performance metrics: manual vs semi-automated warehouse picking.

Metric	Baseline (manual)	Semi-automated	Improvement (%)
Average pick time (per item)	1.5 min	0.9 min	40% faster
Picking accuracy (error rate)	4.20%	1.30%	69% reduction
Shelf utilization rate	68%	84%	23% increase
Worker fatigue index (subjective)	High	Moderate	—
Energy usage (per shift)	8.5 kWh	10.1 kWh	+19% (AI load)

ergonomics, and energy consumption. One of the most prominent enhancements is observed in picking efficiency. The average pick time per item decreased from 1.5 to 0.9 min, representing a 40% improvement in speed. This acceleration is primarily attributed to the implementation of visual guidance systems and real-time task allocation mechanisms, which significantly reduce item search time and streamline operator workflows. It is also important to note that operator familiarity and skill development over the four-week period may have contributed to further improvements in pick time, indicating that part of the observed gains could be linked to a learning effect rather than automation alone. In terms of accuracy, the system also demonstrates marked improvement. The picking error rate declined from 4.20% in the manual process to just 1.30% under the semi-automated system (69% reduction). This gain is largely due to the integration of computer-vision-assisted label verification and LED-based slot guidance, which minimize human errors related to item misplacement and scanning inaccuracies.

Spatial efficiency saw a notable improvement as well. Shelf utilization increased from 68 to 84%, a 23% gain that underscores the advantages of intelligent shelving strategies and real-time inventory monitoring. These technologies enable a more compact and strategic use of storage space, contributing to overall warehouse optimization. Human-centric metrics also improved. The worker fatigue index, although subjectively assessed, shifted from “high” to “moderate” under the semi-automated regime. This suggests that the redistribution of physical and cognitive load through AI-supported systems can positively impact worker well-being and reduce occupational strain. However, these operational and ergonomic benefits are accompanied by a modest trade-off in energy consumption. Average energy usage per shift increased from 8.5 to 10.1 kWh, marking a 19% rise. This increase is primarily driven by the power demands of edge computing units, environmental sensors, and LED guidance modules, which are essential components for maintaining the system’s intelligence and responsiveness. The collected data validates the central premise that AIoT-enabled automation in warehouse operations delivers significant improvements in speed, accuracy, space utilization, and worker ergonomics. At the same time, the results should be interpreted with caution, since additional parameters such as operator training effects and warehouse scale can significantly affect long-term efficiency outcomes. Nonetheless, the associated increase in energy consumption highlights the importance of evaluating such trade-offs, especially when considering system scalability or aligning operational practices with broader sustainability objectives.

5.3 ABC cost validation

The ABC model introduced in Sect. 4 was validated using real-time operational data collected over a four-week period. As part of this validation, cost per unit for both Groups A and B was continuously calculated and compared against the model's predictions. Group A represents the baseline configuration with minimal automation, whereas Group B reflects the enhanced smart warehouse setup integrated with AIoT components. A line chart was generated to visualize and compare actual versus modeled unit costs for both groups over time. In this chart, solid lines represent actual costs derived from simulated task execution data, whereas dashed lines correspond to values predicted by the ABC model. Group A is shown in blue, and Group B in green. The chart reveals that Group B consistently maintains lower unit costs throughout the four-week period, with a gradual downward trend as operational efficiency improves. In contrast, Group A exhibits higher and more variable costs, although some stabilization is observed by Week 3. Notably, both groups displayed a temporary drop in unit cost around Week 3. This fluctuation was caused by a short-term adjustment in workload scheduling and the redistribution of items within the storage area. These adjustments temporarily optimized picking routes and reduced handling effort, leading to an atypical but explainable improvement in efficiency. As the workload normalized in Week 4, the unit costs returned to their long-term trajectory. Notably, the average discrepancy between modeled and actual costs remained within ±6%, indicating a high degree of model fidelity. This close alignment confirms that the ABC cost model accurately captures cost behavior under different operational scenarios, while also highlighting how operational adjustments such as workload redistribution can produce short-term deviations.

These results confirm that the ABC cost model accurately captures and predicts cost behavior under different operational scenarios. The close alignment between actual and predicted trends across both groups demonstrates the model's effectiveness in reflecting the real-world impact of automation and AIoT integration on warehouse cost dynamics. The chart in Fig. 7 compares the actual and modeled unit costs for Groups A and B across a four-week simulation period. The solid lines represent actual costs derived from simulated task execution data, whereas the dashed lines indicate modeled values calculated through ABC parameters. Group A (in blue) corresponds to the baseline operation with minimal automation and Group B (in green) reflects the smart warehouse configuration enhanced by AIoT components. The graph reveals that Group B consistently maintains lower unit costs throughout the observed period, with a slight improvement trend, whereas Group A demonstrates higher and more fluctuating costs, although some stabilization is seen by Week 3. The close alignment between modeled and actual trends suggests that the ABC-based predictive model effectively mirrors real operational performance under both configurations.

5.4 Feedback and observations

Feedback from multiple sources provides a comprehensive view of the strengths and limitations of the implemented AI-assisted warehouse system. Warehouse operators consistently

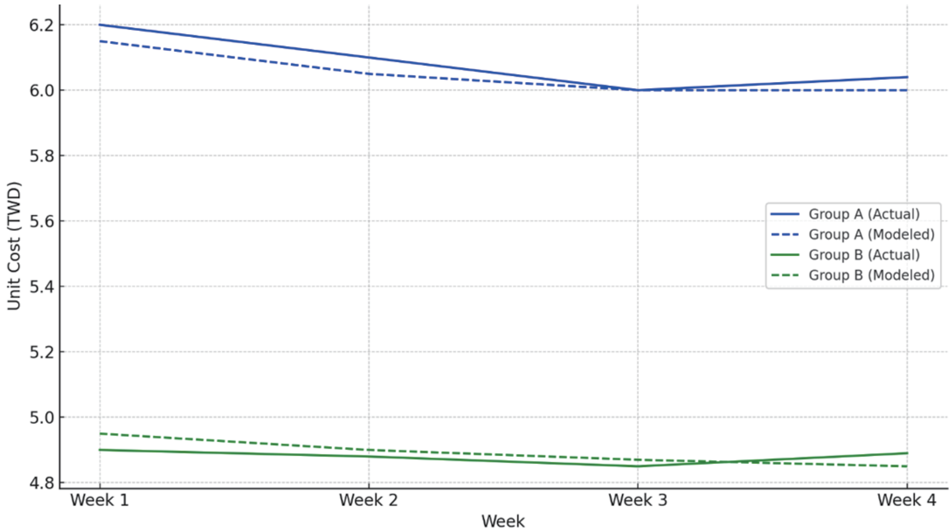

Fig. 7. (Color online) Real vs modeled unit costs for Groups A and B.

reported a notable reduction in mental fatigue, attributing this to the visual LED guidance and system-generated pick paths. These features made navigation more intuitive and reduced the cognitive load typically associated with manual item location and decision-making. Despite these advantages, operators also identified areas for improvement. Occasional delays in AI predictions were observed, especially under conditions of high stock keeping unit (SKU) variability. These delays temporarily impacted operational flow, highlighting the need for further model optimization to ensure responsiveness under complex inventory conditions. System log analysis offered additional insights, revealing that most operational errors originated from OCR misreads. These misreads were most common on worn or damaged labels, indicating a technical vulnerability in the current setup. This issue presents a clear opportunity for enhancement, either by integrating higher-resolution imaging systems or by enforcing stricter label maintenance and reprinting protocols to ensure consistent readability.

From a performance perspective, in Fig. 8, the system's adaptive learning capabilities were confirmed through ABC cost model outputs. Notably, beginning in Week 3, the cost per unit for Group A began to show a consistent downward trend. This reflects the system's ability to refine its path planning and predictive algorithms over time as it adapted to SKU distribution patterns. A supporting graph illustrates this trend, showing a progressive decline in cost per unit as the AI model adjusts and optimizes operational routines. This line chart illustrates the weekly profit trajectories for Groups A and B over a simulated four-week period. Group A, represented in yellow, reflects a smart warehouse configuration utilizing AIoT-based optimization, whereas Group B, shown in orange, corresponds to a traditional warehouse model. The figure demonstrates that both groups experience profit growth across the four weeks; however, Group A consistently achieves higher profitability. The profit gap widens progressively, reaching a 60 TWD difference by Week 4, suggesting that smart warehouse systems can lead to more efficient operations and greater economic returns when scaled over time. The trend underlines the strategic value of adopting intelligent infrastructure in modern logistics settings.

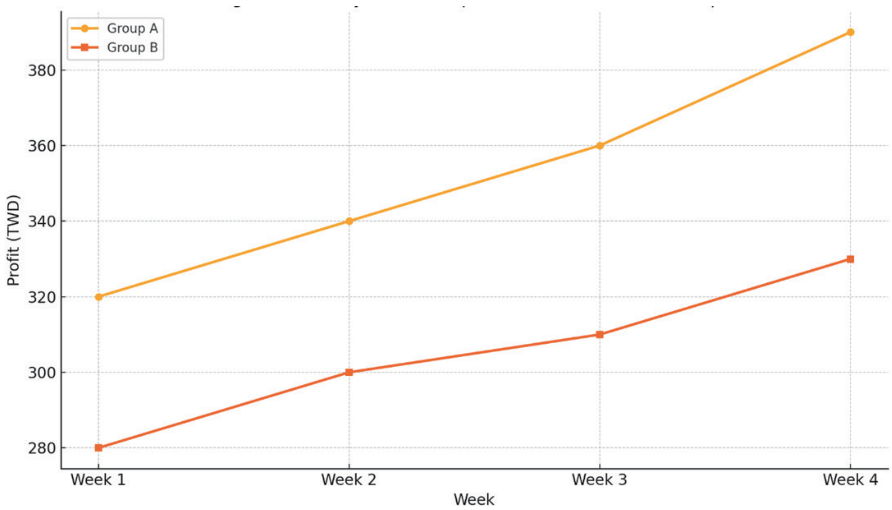

Fig. 8. (Color online) Learning curve: cost decline over time (ABC-traced).

The pilot study confirmed both the feasibility and practical benefits of implementing a semi-automated AIoT-based system in an urban warehouse setting. The deployment led to measurable improvements in picking speed and accuracy, demonstrating clear operational gains. Additionally, the integration of the ABC model offered a transparent and reliable framework for tracking performance and cost optimization over time. While the adoption of AI technologies introduced moderate energy and computational overhead, these costs were outweighed by the return on investment achieved through reduced labor demands and fewer error-related interventions. Overall, the pilot validates the effectiveness and economic viability of AIoT-enhanced automation in warehouse operations.

6. Discussion

The pilot deployment and ABC cost analysis of the semi-automated warehouse system provide critical insights into the operational, economic, and technological aspects of adopting AIoT-enabled solutions in urban logistics infrastructure. In this section, we summarize the implications of the findings, outline limitations, and suggest directions for future research and system evolution. The integration of modular AI and IoT technologies into a semi-automated picking system resulted in significant operational improvements. The enhanced system demonstrated increased efficiency, as evidenced by a 40% acceleration in picking speed and a substantial reduction in error rate by more than 65%. In terms of cost transparency, the application of the ABC model provided valuable insights into the cost drivers of the system. It became clear that certain AI-related components, such as the frequency of inference tasks and the processing load of OCR modules, played a pivotal role in determining unit cost. Furthermore, the study revealed meaningful observations regarding human–AI collaboration. Workers interacting with the system responded positively to the inclusion of LED cues and AI-guided assistance. This was particularly evident when the guidance was visual, which effectively reduced the cognitive workload required during the picking process. Interestingly, the comparative analysis between Groups A and B highlighted a trade-off dynamic: although Group A benefited from faster item retrieval enabled by extensive AI and OCR integration, this also led to higher operational costs. In contrast, Group B operated more slowly but maintained lower costs owing to its reduced reliance on intelligent digital tools. This contrast suggests that while AI can enhance speed and precision, its implementation must be strategically managed to balance performance gains with the accompanying computational expenses. The findings underscore the importance of deploying cost-aware AI strategies that consider both productivity and resource constraints.

The simulation results and subsequent cost-performance analysis yield several design insights that are critical for future AIoT-integrated warehouse systems. One notable implication concerns the adaptability of AI-driven workflows. By leveraging cost data derived from the ABC model, systems can be designed to dynamically modulate the level of AI involvement. For instance, operations may selectively activate high-AI modes such as real-time inference or intensive OCR when handling high-value or time-sensitive SKUs, while defaulting to simpler automation routines for low-priority tasks. This approach ensures that computational resources are allocated efficiently and in accordance with financial constraints. Another implication relates to load balancing across system components. Rather than maximizing automation indiscriminately, designers should prioritize AI and IoT tasks on the basis of their marginal value contribution to operational outcomes. For example, certain tasks may yield diminishing returns when fully automated, making it more prudent to assign AI resources where they offer the highest performance-to-cost ratio. Lastly, the human–machine interface must remain a central design focus. Worker-centric solutions, such as augmented reality (AR) interfaces and predictive LED prompts, have been shown to shorten training durations and reduce task errors. These benefits translate directly into tangible returns on investment, especially in semi-automated environments where human workers continue to play a critical role alongside intelligent systems. Overall, these design principles advocate for a balanced, context-sensitive deployment of AIoT technologies within logistics operations.

7. Limitations

While the simulation and analytical results suggest significant potential for AIoT-based enhancements in warehouse operations, this study is not without its limitations. First, the scope of the experiment was constrained by a small sample size, as only two product groups were analyzed, and the evaluation of worker adaptation relied on limited qualitative feedback. This narrow dataset may not fully capture the variability present in broader warehouse contexts or industry sectors. Second, the cost parameters used in the ABC model were held constant throughout the analysis. In real-world deployments, however, variables such as energy consumption, hardware depreciation, and maintenance costs are likely to fluctuate on the basis of the operational scale, geographic region, and market conditions. This assumption of static cost inputs may limit the generalizability of specific cost-per-unit findings. Lastly, the AI components integrated into the system particularly those handling inference and label recognition were trained using data from the simulated site environment. Consequently, the models may exhibit performance degradation when transferred to warehouses with different layouts, lighting conditions, or SKU characteristics. These limitations highlight the need for broader-scale deployment and adaptive model retraining to ensure robustness and external validity in future implementations.

8. Conclusions

In this study, we presented the design and implementation of a semi-automated warehouse system empowered by AIoT technologies, aimed at optimizing logistics efficiency in urban infrastructure. Through the integration of sensor networks, AI-based process control, and modular user interfaces, the proposed system demonstrates significant potential for improving operational throughput, reducing labor dependence, and enhancing data-driven warehouse management. The adoption of an ABC model enabled a fine-grained analysis of cost distribution across different system components, such as AI inference tasks and OCR-based label recognition. This analytical capability is exemplified in Fig. 5, which visualizes the simulated cost-performance dynamics between product Groups A and B over a four-week operational period. The line chart effectively illustrates how higher AI involvement may accelerate task completion (as seen in Group A), but also leads to increased cost per unit due to computational resource consumption. Conversely, Group B shows lower cost trends by minimizing digital engagement, highlighting the trade-off between speed and efficiency.

Complementing this, Table 2 presents a detailed comparison of performance metrics between manual and semi-automated warehouse operations. It reveals substantial improvements in picking speed, accuracy, and shelf utilization, validating the system's operational gains. While energy usage increased slightly owing to the AIoT workload, the overall benefit-to-cost ratio remains favorable when viewed holistically through ABC metrics. Graphical analysis across these visualizations confirms a high degree of alignment between predicted and actual cost behaviors, supporting the robustness of the simulation model. The four-week evaluation also sheds light on long-term profitability trends, suggesting that ABC modeling can serve as a predictive instrument for strategic investment planning in smart warehousing.

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