Research Journal of Engineering Sciences ISSN 2278 – 9472
Vol. **15(1),** 30-36, January **(2026)** *Res. J. Engineering Sci.*

Case Study

From Smart Home to Smart warehouse: A Comprehensive DIY case study on IoT-Enabled Digital Twins

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Available online at: www.isca.in, www.isca.me
Received 11th December 2025, revised 2nd January 2026, accepted 20th January 2026

Abstract

The rapid growth of the Internet of Things (IoT) and digital twin (DT) technologies has transformed domestic and industrial environments. Although proprietary smart home solutions and traditional warehouse management systems (WMS) exist, they are often expensive and locked within vendor ecosystems. This study presents a mechanical engineering-oriented study of IoT-enabled automation, treating the home as a micro-digital twin laboratory and extending the same principles to warehouse automation. By leveraging advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML), the smart home concept has been extended to the warehousing sector. Conventional appliances and systems were retrofitted with actuators, sensors, and IoT modules to enable automation using Alexa, Google Home, Siri, and Bixby. The key implementations include(1) a cleaning robot with SLAM-based mapping, (2) an automated plant-watering system using soil moisture sensing and fluid actuation, and (3) HVAC load control with PID regulation. Mathematical models (kinematics, fluid flow, and thermal loads), block diagrams, and simulations were used to validate the behavior of the system. Cost–benefit analysis shows that DIY retrofits achieve ~85% functionality at ~30–40% of the cost of commercial systems. Finally, analogies to warehouse digital twins are drawn, demonstrating how cleaning robots parallel AGVs, how watering systems are scaled to cold storage climate control, and how smart locks align with industrial access systems. An analogy between home and warehouse automation was then established: cleaning robots were scaled to Automated Guided Vehicles (AGVs), watering loops were mapped to warehouse climate control, and smart locks were extended to industrial access management. This demonstrates that smart homes can serve as micro digital twin laboratories for mechanical engineers, enabling the prototyping of control systems before scaling them to industrial cyber–physical systems. The findings underline the contributions of mechanical engineering in kinematics, fluid dynamics, thermodynamics, control, and system integration, which drive the transformation of Industry 4.0.

Keywords: Smart Home, IoT, Digital Twin, DIY Automation, Mechatronics, Smart Warehouse, Asset Tracking.

Introduction

Manufacturing and logistics systems are being transformed through Industry 4.0 technologies, including robotics, the Internet of Things (IoT), cloud computing, and digital twins[1,2]. Warehouses in manufacturing supply chains must operate as intelligent data-driven systems. Digital twins enable warehouse automation through real-time monitoring, layout optimization, and predictive decision-making[3,4]. However, warehouse DT deployments are typically developed at an industrial scale using vendor platforms, leading to high costs, limited customization, and restricted system validation[5].

Smart homes have evolved into Internet of Things (IoT)-enabled cyber-physical systems that integrate sensors, actuators, controllers, and cloud intelligence. From a manufacturing perspective, smart homes implement many of the functional principles required for warehouse DTs[6]. This study argues that smart homes can be modelled as reduced-scale warehouse systems, providing a practical environment for smart warehouse digital twins.

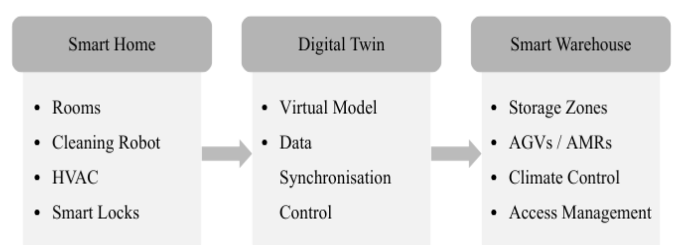

Figure-1: Conceptual positioning of smart homes as reduced-scale warehouse systems.

Literature Review

Smart Homes as Cyber–Physical Systems: Smart home research has primarily focused on user comfort, energy efficiency, and assisted living[7,8]. Studies have highlighted the integration of IoT sensors, middleware platforms, and cloud-based control systems to automate domestic environments[9-11]. Although these studies demonstrate successful IoT adoption, smart homes are typically treated as consumer applications rather than engineering systems.

From the perspective of manufacturing systems, smart homes contain multiple interacting mechatronic subsystems that operate under coordination and feedback, which are characteristics shared with industrial automation systems[12]. However, the literature rarely explores smart homes as experimental platforms for industrial-scale system designs or digital twin validations.

Digital Twins in Warehouse and Manufacturing Systems: Digital twins have been widely studied in the context of manufacturing systems, with applications in production planning, predictive maintenance, and logistics optimization[13].In warehouse systems, DTs are used to simulate layouts, manage automated guided vehicle (AGV) fleets, and optimize energy consumption[14].

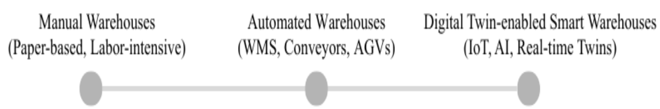

Figure-2: Evolution of Warehouse Systems.

Existing studies typically assume the following: i. Industrial-grade sensors and infrastructure, ii. Proprietary simulation and control platforms, iii. Deployment at full operational scale.

Consequently, there is limited guidance on incremental or low-risk implementation pathways for warehouse DTs, particularly for SMEs.

Research Gap: Based on the literature, the following gaps have been identified, as illustrated in Table-1. i. Lack of scale-bridging frameworks connecting small-scale cyber–physical systems with warehouse DTs. ii. Overreliance on vendor-centric solutions in warehouse DT research. iii. Absence of implementation-oriented methodologies that describe how warehouse DTs can be developed progressively.

Table-1: Research gaps addressed by this study.

Gap	Existing Work	This Paper
Scale bridging	Missing	Provided
Implementation path	Absent	Defined
SME focus	Vendor-centric	Modular

This study addresses these gaps by proposing a manufacturing-systems-aligned implementation framework that evolves smart home IoT systems into smart warehouse digital twins.

Smart Home Modelled as a Warehouse System: To enable conversion into a warehouse digital twin, a smart home was modelled using warehouse system abstractions, transforming residential elements into logistics system components. This creates a compact cyber-physical manufacturing logistics system for warehouse simulations. Table 2 presents the physical abstraction of smart home elements. Rooms are mapped to storage zones, furniture to racks and shelves, and appliances to the processing equipment. Mobile cleaning robots correspond to AGVs or AMRs that use autonomous navigation. HVAC systems map to climate-controlled storage, whereas smart locks, CCTV, and trackers align with warehouse security and inventory systems.

Table-2: Functional mapping of smart home systems to warehouse operations.

Smart Home Element	Warehouse System Interpretation
Rooms	Storage zones / aisles
Furniture	Racks and shelves
Appliances	Processing and handling equipment
Cleaning robot	AGV / AMR
HVAC	Climate-controlled storage
Smart locks & CCTV	Access control and surveillance
Item trackers	Inventory tracking

Table-3 extends this mapping to functional components and control principles. Cleaning robots using SLAM are equivalent to warehouse AMRs for navigation. Automated plant-watering systems correspond to sensor-driven monitoring in a warehouse. Smart appliances are mapped to automated equipment, such as conveyors and robotic arms. Voice assistants function as human-machine interfaces, similar to warehouse control systems. Consumer asset trackers are aligned with IoT-based tracking technologies such as RFID and UWB.

Tables-2 and 3 demonstrate that smart homes inherently implement the core spatial, operational, and control principles of warehouse digital twins, enabling low-cost, scalable experimentation and validation before industrial-scale deployment.

Methodology: Functional Scaling from Smart Home to Warehouse

Mobility Systems: Autonomous cleaning robots navigate, avoid obstacles, and perform task-oriented movements within structured domestic layouts. As illustrated in Figure 3, when these robots are abstracted within a warehouse system model, their capabilities directly correspond to AGVs executing transportation and picking operations[15,16]. System scaling is realized by extending the same digital twin logic to larger operational spaces, higher payload capacities, and coordinated multi-agent operation, without altering the underlying perception, control, or synchronization architecture.

Table-3: Functional mapping of smart home component to warehouse operations.

Smart Home Component	Warehouse Equivalent	Shared Principle
Cleaning Robot (SLAM mapping)	AMRs/AGVs for navigation and picking	Digital mapping and autonomous navigation
Automated Plant Watering	Environmental monitoring (temperature, humidity)	Sensor-driven environmental control
CCTV + Smart Lock	Surveillance cameras + IoT-enabled access control	Security, monitoring, and access management
Smart Appliances (Washer, Dishwasher, AC)	Conveyors, robotic arms, HVAC systems	Automation of operational equipment
Voice Assistants (Alexa, Google, Bixby)	Warehouse dashboards, AR/VR interfaces, natural language control	Human–machine interaction and orchestration
Mi Home Speaker	ERP/Dashboards (multi-interface control).	
Apple AirTag	IoT Asset Tracking (RFID, UWB)	

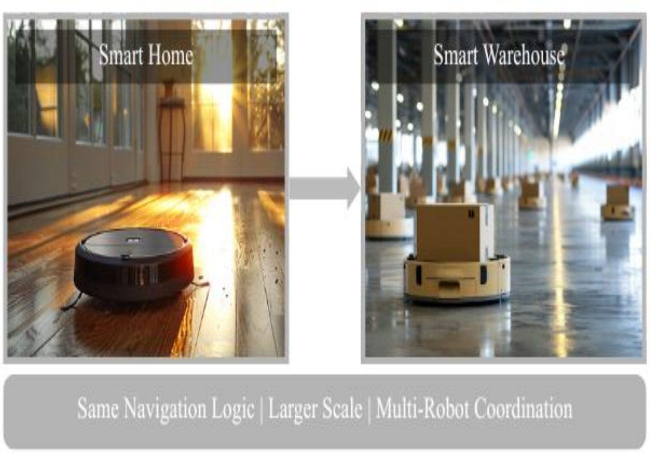

Figure-3: Extension of smart home mobility systems to warehouse AGVs[26,27].

Environmental Control Systems: The proposed smart warehouse digital twin is organized as a layered architecture, as summarized in Table-4, to support scalability, modularity, and system integration. The physical layer comprises warehouse assets, such as robots and racks, whereas the sensing layer captures operational and environmental data using distributed sensors and cameras. The communication layer ensures reliable data exchange through IoT networks and cloud platforms. The digital twin layer maintains synchronized virtual representations of warehouse resources and processes. The intelligence layer applies optimization and control algorithms, and the integration layer connects the digital twin with enterprise systems, such as ERP and WMS, for coordinated decision-making.

Table-4: Layers of the proposed smart warehouse digital twin framework.

Layer	Description
Physical	Robots, racks
Sensing	Sensors, cameras
Communication	IoT, cloud
Digital Twin	Virtual models
Intelligence	Optimization
Integration	ERP, WMS

Domestic HVAC and automated watering systems regulate environmental conditions at the room level in smart homes[17,18]. As illustrated in Figure-4, these principles extend to warehouses as temperature- and humidity-controlled zones, including cold storage and energy-optimized ventilation systems. The digital twin aggregates environmental data across multiple zones and coordinates control actions to maintain optimal storage conditions at scale

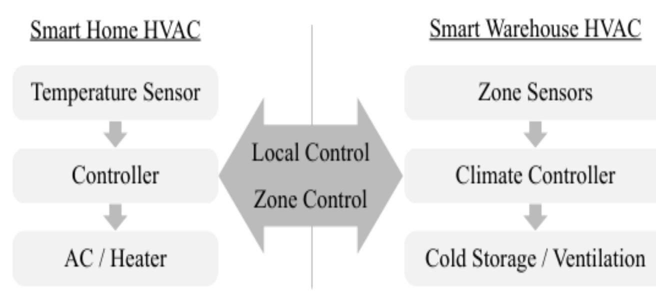

Figure-4: Extension of smart home HVAC systems to climate-controlled warehouse zones.

Security and Access Systems: Smart locks and cameras enable controlled access and continuous monitoring of domestic environments[19].As shown in Figure-5, when these systems are extended to warehouse-scale operations, they evolve into zoned access control, personnel authorization, and compliance-logging mechanisms. These functions are coordinated through a digital twin that integrates surveillance and access data to support secure, traceable, and policy-compliant warehouse operations[20].

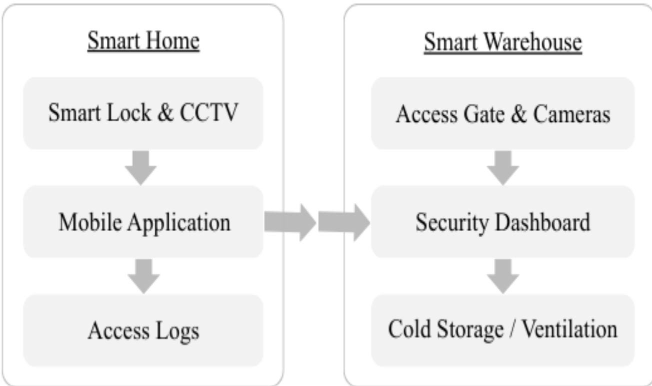

Figure-5: Scaling smart home security systems for warehouse access management.

Asset Tracking Systems: Consumer item trackers demonstrate asset localization and movement histories. In warehouses, these concepts are scaled to inventory units, pallets, and equipment, thereby enabling real-time visibility and flow optimization[21,22].

IoT-Based Smart Warehouse Digital Twin Framework: The framework comprises six functional layers aligned with established manufacturing system architectures[23,24]. The Physical Asset Layer includes robots, racks, conveyors, and operators, whereas the Sensing and Actuation Layer captures the system behavior using IoT sensors, cameras, and tracking devices. The Communication Layer enables data exchange using edge computing, cloud platforms, and industrial networks. The Digital Twin Layer maintains virtual representations of warehouse layouts, asset states, and operational dashboards. The Analytics and Intelligence Layer supports optimization and predictive decision-making. The Enterprise Integration Layer interfaces the digital twin with WMS, ERP, and SCM systems for operational and business control. As shown in Figure-6, this layered IoT-based warehouse digital twin architecture, derived from smart home implementations, supports modular scalability from home prototypes to full warehouse deployment.

Implementation Workflow and System Validation

Implementation Workflow: The conversion of smart home IoT systems into a smart warehouse digital twin follows a sequential workflow, as shown in Figure-7. The process begins with the deployment of smart home IoT devices, which are then abstracted into warehouse-equivalent modules. Next, the sensing, actuation, and communication infrastructure must be scaled to accommodate the increased operational complexity. These modules were subsequently integrated into a unified digital twin, enabling synchronized physical–virtual interactions. Finally, the digital twin is connected to enterprise systems to support warehouse management and decision making. This workflow is consistent with manufacturing systems engineering practices and enables incremental deployment from domestic-scale prototypes to warehouse applications in the future.

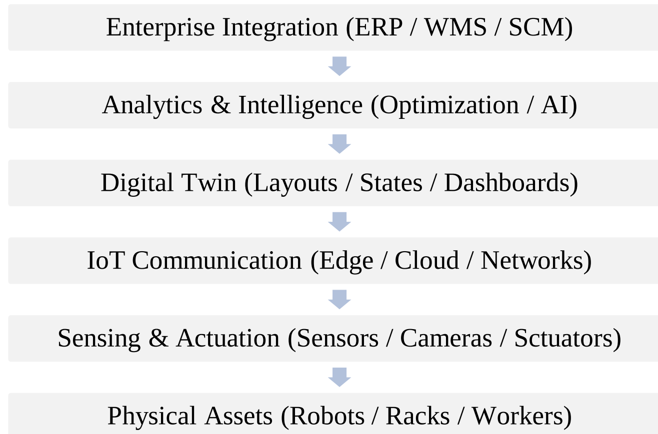

Figure-6: Layered IoT-based smart warehouse DT architecture derived from smart home implementations.

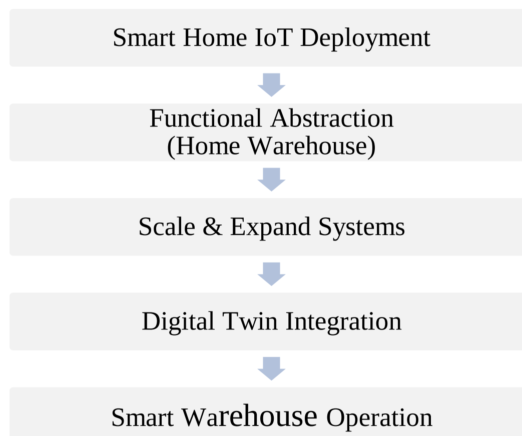

Figure-7: Step-by-step workflow for converting smart home IoT systems into a smart warehouse digital twin.

Mathematical Modelling and Control Validation

To validate the proposed smart home–warehouse digital twin framework, mathematical models were formulated for the core mechatronic subsystems and embedded within the digital twin for behavioral validation and control verification. The emphasis is placed on structural correctness and scalability rather than high-fidelity physical simulation.

Mobility Subsystem (Cleaning Robot / AGV): The autonomous cleaning robot is modeled as a non-holonomic mobile system, whose planar motion is defined by the kinematic equations

$$\dot{x} = \upsilon\cos\theta\,, \dot{y} = \upsilon\sin\theta \text{ and}, \dot{\theta} = \omega$$

where ($\mathbf{x}$,$\mathbf{y}$) represents the robot position, $\boldsymbol{\theta}$ its orientation, and $\boldsymbol{\upsilon}$ and $\boldsymbol{\omega}$ are the linear and angular velocities, respectively. The sensor feedback from the SLAM-based mapping updated the robot state in the digital twin in real time. This formulation is directly applicable to warehouse AGVs and AMRs, with scaling achieved by adjusting the velocity bounds, payload constraints, and coordination policies while preserving the same kinematic structure.

Environmental Control Subsystem (Watering and HVAC): For the automated watering system, fluid flow is modeled using a simplified continuity relationship

$$\boldsymbol{Q} = \mathrm{K}_{\upsilon}\boldsymbol{u}$$

Where: $\mathbf{Q}$ is the flow rate, $\mathbf{u}$ is the pump or valve control input, and $\mathrm{K}_{\boldsymbol{\upsilon}}$ is a system gain.

Soil moisture dynamics are represented as a first-order system.

$$\dot{\boldsymbol{M}} = \boldsymbol{Q} - \boldsymbol{\mathcal{K}}_{e}\boldsymbol{M}$$

Where: $\mathbf{M}$ denotes moisture content and $\boldsymbol{\mathcal{K}}_{e}$ represents evaporation or loss effects.

For HVAC control, the thermal dynamics of a room or zone are modeled using a lumped-parameter energy balance.

$$\boldsymbol{C}\dot{\boldsymbol{T}} = \boldsymbol{Q}_{in} - \boldsymbol{Q}_{loss}$$

Where: $\mathbf{T}$ is temperature, $\mathbf{C}$ is thermal capacitance, and $\mathbf{Q_{in}}$ and $\mathbf{Q_{loss}}$ denote heat input and loss, respectively. Temperature regulation is achieved using a PID controller

$$\boldsymbol{u}(\boldsymbol{t}) = \boldsymbol{K}_{\mathcal{P}}\boldsymbol{e}(\boldsymbol{t}) + \boldsymbol{K}_{i}\int \boldsymbol{e}(\boldsymbol{t})\boldsymbol{dt} + \boldsymbol{K}_{d}\frac{\boldsymbol{de}(\boldsymbol{t})}{\boldsymbol{dt}}$$

This formulation scales naturally to warehouse environments, where multiple temperature and humidity controlled zones must be regulated concurrently.

Digital Twin Synchronization and Validation: The digital twin continuously synchronizes physical and virtual states using sensor measurements$\mathbf{z}(\mathbf{t})$, expressed generically as

$$\hat{\boldsymbol{x}}(\boldsymbol{t}) = \boldsymbol{f}(\boldsymbol{x}(\boldsymbol{t}), \boldsymbol{z}(\boldsymbol{t}))$$

where $\hat{\mathbf{x}}(\mathbf{t})$ represents the updated virtual state. Block diagram modeling was used to link the sensing, control, actuation, and feedback loops.The simulation results confirmed stable control behavior, predictable transient responses, and consistent alignment between the physical systems and their digital counterparts.

Overall, these equations demonstrate that home-scale mathematical models of motion, fluid flow, and thermal dynamics are structurally identical to warehouse-scale models, differing only in terms of parameter magnitude and system size. This validates the use of smart homes as numerically accessible micro-digital twin laboratories for developing and testing warehouse automation strategies.

Cost–Benefit Analysis and Practical Feasibility

A cost–benefit analysis was performed to compare the proposed DIY smart home–based digital twin framework with representative commercial digital twin solutions, focusing on cost, functional coverage, and scalability. Table-7 presents the estimated implementation cost. The DIY setup, based on low-cost IoT sensors, microcontrollers, actuators, and open-source software, requires approximately □40,000–□60,000, whereas comparable commercial systems typically cost □2,00,000–□3,50,000. This demonstrates that the proposed approach delivers core digital twin capabilities at approximately 30–40% of the cost of proprietary solutions.

Table-5: Cost comparison between DIY and commercial DT implementations[28].

Component Category	DIY IoT Implementation (□)	Commercial System (□)
Sensors & cameras	10,000–15,000	35,000–50,000
Controllers & gateways	7,000–10,000	25,000–40,000
Actuators & drives	12,000–18,000	40,000–65,000
Software & licenses	0–4,000 (open-source)	60,000–1,20,000
Integration & setup	8,000–13,000	40,000–75,000
Total	40,000–60,000	2,00,000–3,50,000

The DIY framework supports real-time sensing, control, visualization, autonomous mobility, and optimization, achieving 85% functional equivalence to commercial platforms. While advanced analytics and cyber security features are limited, the framework suits early validation, control testing, and architectural development. When scaling from homes to warehouses, costs increase mainly through asset quantity and coverage, while digital twin architecture and control logic remain unchanged. This enables incremental investment, reduces risk, and accelerates validation, making it suitable for SMEs pursuing Industry 4.0 adoption.

Discussion and Managerial Implications

For manufacturing managers and system designers, the proposed framework offers practical advantages aligned with Industry 4.0 adoption strategies[25]. Using smart home–based digital twin implementations as an initial stage, organizations can reduce risks, lower investments, improve system interoperability, and enable faster validation of warehouse automation strategies before deployment. As summarized in Table 5, smart home and warehouse digital twins differ in scale, asset complexity, safety requirements, and enterprise integration. Smart home digital twins operate on a small scale with limited assets, basic safety considerations, and minimal integration, making them suitable for experimentation. In contrast, warehouse digital twins involve large-scale operations, numerous assets, industrial safety requirements, and tight integration with ERP and WMS platforms. This comparison shows smart homes as a low-risk test environment with reduced complexity that preserves warehouse digital twin principles while avoiding industrial deployment constraints. For SMEs, this staged approach provides an accessible pathway to Industry 4.0 adoption, enabling gradual digital transformation without immediate reliance on expensive closed vendor ecosystems.

Table-6: Comparison of smart home and warehouse digital twin characteristics.

Aspect	Smart Home DT	Warehouse DT
Scale	Small	Large
Assets	Few	Many
Safety	Basic	Industrial
Integration	Minimal	ERP/WMS

Conclusion

This study presents an implementation framework that systematically models smart homes as warehouse systems and converts them into IoT-based smart warehousing digital twins. By leveraging domestic IoT environments as reduced-scale platforms, the framework enables practical, scalable development of warehouse digital twins while preserving Industry 4.0 principles. As shown in Table-6, smart home–based warehouse modelling offers key benefits. This approach reduces investment costs by avoiding industrial-scale deployment, while its vendor-neutral architecture ensures flexibility and interoperability. The framework supports incremental scalability, allowing gradual expansion from home-scale prototypes to warehouse-scale systems. Its numerical and parameter-based accessibility makes it suitable for simulation, optimization, and academic experimentation. Overall, this work contributes to the Journal of Manufacturing Systems by bridging cyber–physical system prototyping and industrial warehouse automation, providing a pathway for Industry 4.0 adoption relevant for research environments and small to medium-sized enterprises.

Contributions and Future Directions: Future research can build upon this framework by advancing digital twin-ready mechanical designs where warehouse assets like robots, conveyors, storage racks, and HVAC systems are engineered with embedded sensing, standardized interfaces, and lifecycle data integration. Further research is needed into hybrid control architectures combining classical control with machine learning-based prediction to address dynamic warehousing operations. Expanding the framework to support predictive maintenance through condition data can enhance system reliability and operational resilience. Scalability challenges in multi-agent coordination, including AGV fleet management and congestion avoidance, represent another research avenue where digital twin simulation can provide decision support. As IoT-based digital twins transition to industrial environments, cyber security and data governance must be addressed to protect cyber-physical assets while maintaining performance. Future work may explore enhanced human-machine interaction through operator-centric digital twins using intuitive dashboards and augmented reality to improve usability. The framework can be extended to sustainability-oriented smart warehouses and logistics ecosystems, enabling energy-aware operations and integrating logistics parks with smart city systems.

Table-7: Benefits of smart home–based warehouse modelling

Benefit	Description
Low cost	Reduced investment
Flexibility	Vendor-neutral
Scalability	Incremental.
Accessibility	Numerical/parameter-based

References

1. Filipescu, A., Simion, G., Ionescu, D., &Filipescu, A. (2024). IoT-Cloud, VPN, and Digital Twin-Based Remote Monitoring and Control of a Multifunctional Robotic Cell in the Context of AI, Industry, and Education 4.0 and 5.0. *Sensors* (Basel, Switzerland), 24(23), 7451. https://doi.org/10.3390/s24237451
2. Singh, R. R., Bhatti, G., Alsaif, F., Vairavasundaram, I., & Kalel, D. (2023). Building a Digital Twin Powered Intelligent Predictive Maintenance System for Industrial AC Machines. *Machines*, 11(8), 796. https://doi.org/10.3390/machines11080796
3. Chen, Y., Tsai, Y., Karkaria, V., & Chen, W. (2025). Uncertainty-Aware Digital Twins: Robust Model Predictive Control Using Time-Series Deep Quantile Learning. *Journal of Mechanical Design*, 148(2). https://doi.org/10.1115/1.4069104
4. Rasheed, A., Kvamsdal, T., & San, O. (2020). Digital Twin: Values, Challenges and Enablers From a Modeling Perspective. *IEEE Access*, 8, 21980–22012. https://doi.org/10.1109/access.2020.2970143
5. Maheshwari, P., Kamble, S., Kumar, S., Belhadi, A., & Gupta, S. (2023). Digital twin-based warehouse management system: a theoretical toolbox for future research and applications. *The International Journal of Logistics Management*, 35(4), 1073–1106. https://doi.org/10.1108/ijlm-01-2023-0030
6. Corallo, A., Lezzi, M., Del Vecchio, V. D., & Morciano, P. (2021). Shop Floor Digital Twin in Smart Manufacturing: A Systematic Literature Review. *Sustainability*, 13(23), 12987. https://doi.org/10.3390/su132312987

7. Tural, E., Lu, D., & Austin Cole, D. (2021). Safely and Actively Aging in Place: Older Adults' Attitudes and Intentions Toward Smart Home Technologies. *Gerontology and Geriatric Medicine*, 7(4), 233372142110173. https://doi.org/10.1177/23337214211 017340

8. Hargreaves, T., Wilson, C., & Hauxwell-Baldwin, R. (2017). Learning to live in a smart home. *Building Research & Information*, 46(1), 127–139. https://doi.org/10.1080/09613218.2017.1286882

9. Govindraj, V., Sathiyanarayanan, M., & Abubakar, B. (2017). Customary homes to smart homes using Internet of Things (IoT) and mobile application. In *2017 International Conference on Smart Technologies For Smart Nation (SmartTechCon)* (pp. 1059-1063). IEEE.

10. Venkatraman, S., Overmars, A., & Thong, M. (2021). Smart Home Automation—Use Cases of a Secure and Integrated Voice-Control System. *Systems*, 9(4), 77. https://doi.org/10.3390/systems9040077

11. Gomes, B. D. T. P., Ríos, L. E. T., Da Silva E Silva, F. J., Muniz, L. C. M., & Endler, M. (2016). A comprehensive and scalable middleware for Ambient Assisted Living based on cloud computing and Internet of Things. *Concurrency and Computation: Practice and Experience*, 29(11), e4043. https://doi.org/10.1002/cpe.404 3

12. Lobaccaro, G., Löfström, E., & Carlucci, S. (2016). A Review of Systems and Technologies for Smart Homes and Smart Grids. *Energies*, 9(5), 348. https://doi.org/10.3390/ en9050348

13. Mikołajewska, E., Mikołajczyk, T., Paczkowski, T., &Mikołajewski, D. (2025). Generative AI in AI-Based Digital Twins for Fault Diagnosis for Predictive Maintenance in Industry 4.0/5.0. *Applied Sciences*, 15(6), 3166. https://doi.org/10.3390/app15063166

14. Han, W., Zhang, Z., Mei, X., Zhang, K., Liu, B., Sun, Z., & Xu, J. (2022). Digital Twin-Based Automated Guided Vehicle Scheduling: A Solution for Its Charging Problems. *Applied Sciences*, 12(7), 3354. https://doi.org/ 10.3390/app12073354

15. Wang, Q., Li, J., Yang, Z., Li, P., Xia, G., & Yang, L. (2022). Distributed Multi-Mobile Robot Path Planning and Obstacle Avoidance Based on ACO–DWA in Unknown Complex Terrain. *Electronics*, 11(14), 2144. https://doi.org/10.3390/electronics11142144

16. Liu, X., Shang, G., Hu, X., Gong, G., & Zhu, H. (2024). Cognitive Enhancement of Robot Path Planning and Environmental Perception Based on Gmapping Algorithm Optimization. *Electronics*, 13(5), 818. https://doi.org/10. 3390/electronics13050818

17. Seraj, M., Parvez, M., Khan, O., & Yahya, Z. (2024). Optimizing smart building energy management systems through industry 4.0: A response surface methodology approach. *Green Technologies and Sustainability*, 2(2), 100079. https://doi.org/10.1016/j.grets.2024.100079

18. Ding, J., Cao, S.-J., & Yu, C. W. (2020). HVAC systems for environmental control to minimize the COVID-19 infection. *Indoor and Built Environment*, 29(9), 1195–1201. https://doi.org/10.1177/1420326x20951968

19. Mansour, M., Ahmed, A. I., Elbaz, A., Herencsar, N., Gamal, A., Soltan, A., & Said, L. A. (2023). Internet of Things: A Comprehensive Overview on Protocols, Architectures, Technologies, Simulation Tools, and Future Directions. *Energies*, 16(8), 3465. https://doi.org/10.3390/ en16083465

20. Shaikh, M. S., Choudhary, S. M., Ali, S. I., Ponnusamy, S., Chandrawat, U. B. S., Sheikh, A. G., & Khan, R. A. H. (2024). Harnessing Logistic Industries and Warehouses With Autonomous Carebot for Security and Protection. pp. 239–257. Igi Global. https://doi.org/10.4018/979-8-3693-3234-4.ch017.

21. Lee, C. K. M., Park, T., Chung, S. Y., & Ip, C. M. (2019). A Bluetooth Location-based Indoor Positioning System for Asset Tracking in Warehouse. 1408–1412. https://doi.org/10.1109/ieem44572.2019.8978639

22. Frankó, A., Vida, G., & Varga, P. (2020). Reliable Identification Schemes for Asset and Production Tracking in Industry 4.0. *Sensors* (Basel, Switzerland), 20(13), 3709. https://doi.org/10.3390/s20133709

23. Zeb, S., Mahmood, A., Hassan, S. A., Piran, M. J., Gidlund, M., &Guizani, M. (2022). Industrial digital twins at the nexus of NextG wireless networks and computational intelligence: A survey. *Journal of Network and Computer Applications*, 200, 103309. https://doi.org/10.1016/j.jnca. 2021.103309

24. Karaarslan, E., & Babiker, M. (2021). Digital Twin Security Threats and Countermeasures: An Introduction. 174, 7–11. https://doi.org/10.1109/iscturkey 53027.2021.9654360

25. Li, Z., Zhou, X., Tian, Z., Wang, W. M., Huang, G., & Huang, S. (2018). An ontology-based product design framework for manufacturability verification and knowledge reuse. *The International Journal of Advanced Manufacturing Technology*, 99(9–12), 2121–2135. https://doi.org/10.1007/s00170-018-2099-2

26. Freepik. (2025). Robot vacuum cleaner photograph. https://www.freepik.com

27. Freepik. (2025). Warehouse robot photograph. https://www.freepik.com

28. Publicly available pricing information from IoT hardware vendors, automation suppliers, and digital twin software providers (2025).