Advances in Business & Industrial Marketing Research

Volume 4, Issue 2 (2026). 182-196

e-ISSN: 2985-7589

DOI: https://doi.org/10.60079/abim.v4i2.856

Smart Warehouse Ecosystem: An IoT-Based Framework for Real-Time Environmental Monitoring in a Nutrition Fulfillment Service Unit (SPPG) Warehouse

Geby Ayu Fadhilah [1*] Ginandia Ariesta [2] Ahmad Rufa'i [3] Deddy Rusdiansyah [4] Syarif Hidayat [5]

[1*, 2, 3, 4, 5] Universitas Primagraha, Serang, Indonesia.

Email: gebyayufadhilah@gmail.com, ginandia12@gmail.com, ahmadrufai@gmail.com, deddyrusdiansyah@gmail.com, syarifh@gmail.com

ARTICLE HISTORY

Submitted : May 21, 2026
Reviewed : May 26, 2026
Revised : May 29, 2026
Accepted : May 30, 2026
Published : May 31, 2026

Conflict of Interest Statement:
The author(s) declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

ABSTRACT

Purpose: This conceptual and simulation-based study aims to examine the potential digital transformation of the logistics system at the Kasemen SPPG Warehouse. It specifically investigates the ability of RFID integration to reduce inaccuracies in food inventory data, evaluates the responsiveness of an IoT-based network architecture using the MQTT protocol for environmental early-warning transmission, and measures automation-driven cycle-time efficiency in inbound and outbound logistics processes.

Research Method: This study applies a Research and Development (R&D) approach, focusing on conceptual framework design and performance evaluation using secondary data. The analysis includes Inventory Record Inaccuracy (IRI) measurement using RMSE, evaluation of notification responsiveness via MQTT transmission delay, and time-motion analysis of inbound and outbound cycles, supported by an automated FEFO algorithm.

Results and Discussion: The simulation results provide preliminary conceptual support for the proposed operational hypotheses. IRI decreased by 88.86%, from 6.91 to 0.77 RMSE units. Notification responsiveness improved by 99.98%, from 21,600 seconds in the manual system to 2.2 seconds using MQTT. Automation also reduced cycle time by 92.59% in inbound activities and 93.33% in outbound activities.

Implications: The findings offer a practical blueprint for shifting warehouse operations from reactive to preventive, reducing the risk of food waste, and supporting digitally standardized logistics SOPs.

Originality: This study presents an integrated IoT-based Smart Warehouse model that combines RFID, MQTT, and automated FEFO to support food logistics decision-making.

Keywords: smart warehouse; internet of things; inventory record inaccuracy; notification responsiveness; cycle time.

1. Introduction

In the Industry 4.0 era, the role of warehouses has undergone a fundamental transformation from mere passive storage into a strategic element that determines overall supply chain efficiency (Tiwari, 2023). The adoption of smart technologies in warehousing aims to enhance service quality, productivity, and efficiency while simultaneously minimizing costs and operational failure rates (van Geest *et al.*, 2021). This is highly relevant in safeguarding national food logistics, particularly in supporting strategic government initiatives such as the Makan Bergizi Gratis (Free Nutritious Meal) program, which requires exceptionally high food safety standards. The Nutritious Feeding Service Unit (SPPG) Warehouse in Kasemen District, Serang City, represents a crucial node in this program's distribution chain. However, current operations at the SPPG Warehouse are still categorized as traditional.

In traditional systems, environmental monitoring, such as temperature and humidity, is often neglected or conducted only periodically, posing a significant risk of quality degradation for sensitive food commodities. The geographical conditions of Serang City, characterized by relatively high ambient humidity, present additional challenges for food storage at the Kasemen SPPG. Without an integrated monitoring system, the risks of microbial contamination and food spoilage escalate dramatically. Furthermore, the manual recording system currently implemented at the SPPG is not only susceptible to human error but also creates bottlenecks in the information integration required for rapid decision-making in food logistics management (Fernando *et al.,* 2024). To address the limitations of traditional warehousing, recent studies have explored the deployment of modern technologies. As highlighted by Affia and Aamer (2022), real-time visibility and traceability represent primary challenges in traditional warehousing that can be effectively mitigated through Internet of Things (IoT)-based infrastructure. Furthermore, real-time data integration via IoT sensors has been shown to enable the early detection of environmental anomalies that could compromise the nutritional integrity of food (Sahara & Aamer, 2022).

Prior research demonstrates that implementing a Smart Warehouse architecture provides more robust monitoring management through the use of continuously operating sensor devices and data collection units (Khan *et al.,* 2022). The deployment of this IoT technology enables autonomous environmental monitoring, in which any parameter fluctuations can be addressed immediately via automated notifications to maintain the stability of stored commodities (Selvaraj & Anusha, 2021). Although extensive research has been conducted on IoT-based smart warehouses (Khan *et al.,* 2022; Selvaraj & Anusha, 2021), a significant research gap remains. Most systems developed in previous studies remain passive, wherein IoT functions merely as a static monitoring tool without providing dynamic operational guidance. Furthermore, existing systems fail to integrate environmental monitoring with stock management for fast-moving food items, despite these characteristics being highly dominant in SPPG operations, which demand a continuous supply of daily nutritious meals.

This study aims to investigate the design of an IoT-based Smart Warehouse system tailored for environmental condition monitoring at the Kasemen District SPPG Warehouse. The novelty of this research lies in the development of a multi-sensor IoT data integration framework that automatically links environmental parameters and stock identification into a decision-support database. Unlike conventional models, this framework is specifically designed as a digital quality assurance instrument that transforms IoT's role from a mere monitoring tool into an instantaneous operational risk mitigation system. Through this design, the SPPG Warehouse is expected to transition to an intelligent, transparent system to ensure accountability for food quality while minimizing food waste.

To provide a clear overview, the remainder of this paper is structured as follows. Section 2 (Literature Review and Hypothesis Development) presents the theoretical foundation and hypotheses derived from recent studies. Section 3 (Research Methodology) details the conceptual framework, the integration of secondary data, and the performance projection metrics used in this study. Section 4 (Results and Discussion) presents the architectural evaluation, comparative simulation analysis based on parameters from the literature, and managerial implications. Finally, Section 5 (Conclusion) summarizes the primary findings and offers directions for future research.

2. Literature Review and Hypothesis Development

2.1 Literature Review

Warehouse transformation in the Industry 4.0 era has fundamentally shifted from traditional, static storage functions into a strategic element that determines overall supply chain efficiency (Tiwari, 2023). The adoption of smart technologies in warehousing ecosystems (smart warehouses) has been shown to enhance service quality, productivity, and efficiency while reducing operational failure rates (van Geest *et al.,* 2021). This digitalization becomes highly critical in vital sectors such as national food logistics, which demand stringent quality and safety standards, particularly in supporting strategic initiatives for national nutrition standard assurance (Tiwari, 2023)

In the context of storing sensitive, fast-moving commodities, conventional warehousing frequently encounters spoilage risks due to a lack of transparency in micro-environmental data (Sahara & Aamer, 2022). Consequently, the contemporary academic landscape has shifted its focus toward leveraging integrated Internet of Things (IoT) architectures to bridge the gap between physical stock records and the actual conditions of storage spaces (Fernando *et al.,* 2024).

The evolution of thought regarding logistics warehouse operations indicates that reliance on manual monitoring constitutes a primary structural challenge that triggers susceptibility to human error (Fernando *et al.,* 2024). Affia and Aamer (2022) emphasize that real-time visibility and traceability are the most significant bottlenecks in traditional warehousing and can only be resolved through the deployment of IoT-based infrastructure. Aligning with this view, Sahara and Aamer (2022) demonstrated that real-time data integration via wireless sensors facilitates early detection of environmental anomalies that could compromise food nutritional quality.

Although numerous researchers have validated the efficiency of IoT-based smart warehouse architectures (Khan *et al.,* 2022; Selvaraj & Anusha, 2021), a critical evaluation of the literature reveals fundamental limitations. The majority of systems developed by Khan *et al.,* (2022) and Selvaraj and Anusha (2021) still position IoT as a passive, unidirectional monitoring tool. Furthermore, an adaptive integration that automatically links environmental parameter fluctuations with the stock management of fast-moving commodities remains absent, even though operational response delays in food warehouses directly result in catastrophic raw material spoilage (Sahara & Aamer, 2022)

To address this gap, this study is grounded in the Industry 4.0 Reference Architecture Framework developed by van Geest *et al.,* (2021). This framework integrates the interaction between physical devices and digital information systems through three structured functional layers.

- ***Perception Layer*****:** It integrates physical DHT22 sensors to capture thermal stability alongside a Radio Frequency Identification (RFID) module for the autonomous timestamping of stock entry to drive the First Expired, First Out (FEFO) algorithm (Sahara & Aamer, 2022).
- ***Network Layer:*** It utilizes an ESP32 microcontroller as a communication gateway running the MQTT (Message Queuing Telemetry Transport) protocol. According to Khan *et al.,* (2022), the lightweight architecture of MQTT ensures data transmission continuity in bandwidth-constrained environments.
- ***Application Layer:*** It features an interactive dashboard serving as a Decision Support System (DSS) to process integrated environmental and stock data into instantaneous risk mitigation instructions (van Geest *et al.,* 2021)

2.2 Hypothesis

2.2.1 IoT Multi-Sensor Integration and Stock Accuracy

In traditional warehouse management, manual recording often leads to inefficiencies due to inaccuracies in stock information (Fernando *et al.,* 2024). The implementation of RFID-based automated labeling, combined with continuous data collection units, can minimize these recording deviations (Khan *et al.,* 2022). To rigorously assess the reliability of this data integration, the Root Mean Squared Error (RMSE) is used as the primary evaluation metric because it is highly sensitive to large errors between actual field data and system data (Kolassa, 2026). Based on these arguments, the following hypothesis is proposed:

H1: *Sensor integration within the IoT-based Smart Warehouse architecture significantly minimizes the Root Mean Squared Error (RMSE) value of food stock data recording at the SPPG Warehouse.*

2.2.2 Environmental Monitoring and System Responsiveness

Geographical conditions in regions with high ambient humidity pose significant challenges by accelerating food spoilage (Sahara & Aamer, 2022). Autonomous monitoring of micro-environmental conditions via IoT devices enables early detection, allowing prompt action in response to parameter fluctuations through automated notifications (Selvaraj & Anusha, 2021). By deploying the MQTT communication protocol, which exhibits low-latency characteristics at the network layer (Khan *et al.,* 2022), data transmission bottlenecks can be eliminated, thereby enhancing system responsiveness. Based on these arguments, the following hypothesis is proposed:

H2: *The implementation of an MQTT protocol-based network architecture significantly enhances system responsiveness in detecting and providing notifications for environmental anomalies at the SPPG Warehouse.*

2.2.3 Decision Support System and Operational Efficiency

The transformation of IoT functionality from a mere data-recording tool to an operational decision-support system lies at the core of modern warehousing efficiency (van Geest *et al.,* 2021). When data from the perception layer is successfully converted by the Decision Support System (DSS) components into dynamic FEFO-handling instructions, operators can execute instantaneous corrective actions before food quality degrades (Sahara & Aamer, 2022). This rapid integration of information is highly critical for bypassing bureaucratic delays and enhancing productivity (Fernando *et al.,* 2024). Based on these interrelations, the following hypothesis is proposed:

H3: *The implementation of a Decision Support System (DSS) within the Smart Warehouse significantly enhances operational efficiency by minimizing the risk of stock-handling delays and food waste at the SPPG Warehouse.*

3. Research Method

3.1 The study design

This study employs a Research and Development (R&D) approach, focusing on the conceptual framework design stage and performance evaluation based on secondary data (van Geest *et al.,* 2021). Unlike direct physical testing, this research design adopts a theoretical evaluation method to assess the efficiency of the smart warehouse system (Khan *et al.,* 2022). The research procedure is systematically carried out in three main stages, derived from the Industry 4.0 reference architecture (van Geest *et al.,* 2021). The first stage involves identifying operational issues at the Kasemen SPPG Warehouse using real-world field data (Affia & Aamer, 2022). Baseline warehouse data were gathered during a single on-site visit in April 2026, comprising approximately two hours of direct layout observation and a semi-structured interview with one warehouse coordinator and two operational staff. Manual cycle-time values reported in this study reflect informants' self-reported averages rather than repeated time-motion measurements; this is acknowledged as a methodological limitation. The second stage comprises the design of technical specifications and data integration workflows across the perception, network, and application layers (van Geest *et al.,* 2021). It should be emphasized that this evaluation is simulation-based; the procedure does not include physical implementation, field experimentation, or repeated time-motion measurement at the Kasemen SPPG Warehouse. The third stage conducts performance evaluation simulations by adopting empirical performance parameters (such as processing time, latency, and accuracy rates) validated in prior literature to measure the projected efficiency of the designed system (Kolassa, 2026; Khan *et al.,* 2022)

3.2 Subject Research

The object of evaluation in this study is the system implementation plan for the Satuan Pelayanan Pelayanan Bergizi (SPPG) Warehouse in Kasemen District, Serang City. The data used in this research consist entirely of secondary data sourced from reputable scientific literature, technical reports, and international journal articles that address the performance of similar hardware (Khan *et al.,* 2022; van Geest *et al.,* 2021). The system components evaluated conceptually include DHT22 sensors for thermal stability, Radio Frequency Identification (RFID) technology for stock labeling, an ESP32 microcontroller, and the MQTT communication protocol (Sahara & Aamer, 2022; Khan *et al.,* 2022). Performance specifications for each component, such as RFID read speeds and MQTT data transmission latency, are extracted from the experimental results of prior studies to serve as a baseline reference for efficiency calculations (Khan *et al.,* 2022)

3.3 Data Collection Techniques and Instrument Development

Data collection techniques are categorized into two primary phases (Affia & Aamer, 2022). First, baseline warehouse conditions are gathered through preliminary layout observations and informal interviews with operational management at the Kasemen SPPG. The authors acknowledge that this manuscript does not yet report a full empirical protocol — specifically, the number and role of respondents, the duration and frequency of field observations, the sampling logic for commodity selection, and the data-validation procedure are not exhaustively documented and constitute a methodological limitation that should be addressed in a follow-up empirical study. Baseline warehouse conditions are gathered through layout observations and interviews with the operational management at the Kasemen SPPG to identify traditional problem variables, such as manual logging durations and food waste risks (Fernando *et al.,* 2024). Second, technological performance parameters are compiled through an extensive literature review (Khan *et al.,* 2022). The evaluation instrument is developed by establishing baseline reference parameters derived from the literature (van Geest *et al.,* 2021). For instance, the duration of stock mutation logging via RFID is set at a constant of 2 seconds, based on the average autonomous

Advances in Business & Industrial Marketing Research
OPEN ACCESS
Volume 4, Issue 2 (2026). 182-196
e-ISSN: 2985-7589
DOI: https://doi.org/10.60079/abim.v4i2.856

read speed reported in similar studies; this value is subsequently compared against the actual manual recording duration at the Kasemen SPPG Warehouse (Khan *et al.,* 2022)

3.4 Data Analysis and Evaluation Techniques

Data analysis techniques are oriented toward testing hypotheses through comparative analysis between the existing traditional system and the proposed IoT-based Smart Warehouse system (van Geest *et al.,* 2021). Testing the stock accuracy dimension is conducted by applying the Root Mean Squared Error (RMSE) analysis method, referencing the methodology of Kolassa (2026) [Note: the accessibility and final publication status of Kolassa (2026) and Glock *et al.,* (2025) should be re-verified by the authors prior to final submission], wherein deviation values are calculated based on a simulated comparison between manual recording errors in the field and the automated RFID error tolerance limits derived from the literature. For the responsiveness and operational efficiency dimensions, the analysis is carried out descriptively and comparatively using time-motion analysis (Fernando *et al.,* 2024). Efficiency is measured by the magnitude of the reduction in process time achieved when the manual system (derived from SPPG interview data) is replaced with automated time estimates based on literature parameter data (Sahara & Aamer, 2022; Fernando *et al.,* 2024). The results of this analysis are ultimately used to validate the extent to which the Decision Support System (DSS) can theoretically mitigate operational risks (van Geest *et al.,* 2021).

Table 1. Variables and Measurements

Variable	Measure	Operational Definition / Formula	Source
Information Accuracy	Inventory Record Inaccuracy (IRI)	Measuring the level of data inaccuracy via the Root Mean Squared Error (RMSE) statistical deviation formula. $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2}$	(Glock *et al.,* 2025; Kolassa, 2026)
Operational Efficiency	Cycle Time	Measuring the total cycle time of inbound goods data logging activities using the work-time efficiency formula (Et): $E_t = \frac{T_{Manual} - T_{System}}{T_{Manual}} \times 100\%$	(Heizer & Render, 2014)
System Responsiveness	Notification Responsiveness	Measuring environmental anomaly detection and transmission speed based on cumulative latency response time: $T_{Respond} = t_{sensing} + t_{transmit} + t_{dss}$	(Selvaraj & Anusha, 2021)

4. Results and Discussion

4.1 Analysis Results

The data analysis process in this study is oriented toward evaluating the effectiveness of the integrated operational framework within the Internet of Things (IoT)-based Smart Warehouse system. The formulation of these evaluation parameters takes into account the alignment between the system's technical capabilities and the warehouse's operational needs. This approach is adopted to ensure that the measurement results accurately reflect system performance and support more effective managerial decision-making at the Kasemen SPPG Warehouse. By integrating data from the perception layer into the decision support dashboard, the efficiency of the proposed system design is rigorously measured using three primary parameters: Inventory Record Inaccuracy (IRI), Cycle Time, and Notification Responsiveness.

4.1.1 Analysis of Inventory Record Inaccuracy (IRI) Calculation

Testing of the first parameter is conducted to measure the level of inventory record inaccuracy between physical warehouse conditions and the administrative system (Glock *et al.,* 2025). Referencing the methodology of Kolassa (2026), this reliability evaluation is calculated using the Root Mean Squared Error (RMSE) statistical approach to detect large-magnitude recording errors through the following formulation sensitively:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2}$$

Where Ai represents the actual physical stock volume in the field, Fi denotes the stock volume recorded in the warehouse administrative system, and n is the number of daily inventory observation samples for fast-moving goods

Based on preliminary observation data from the traditional warehousing system at the Kasemen SPPG, a simulation sample of n = 5 types of daily food commodities was selected. Due to the limitations of manual recording, a consistent discrepancy was observed between physical warehouse inventory and stock card bookkeeping (Fernando *et al.,* 2024). It must be acknowledged that the choice of n = 5 commodities is illustrative rather than empirically derived: the manuscript does not document the sampling logic, the selection criteria, or whether these five commodities are representative of the broader daily food inventory at the Kasemen SPPG. The 88.86% RMSE reduction reported below should therefore be read as an illustrative calculation, not as strong empirical evidence of system performance. To test Hypothesis 1 (H1), a comparative error-value simulation was conducted between the existing traditional system and the projected RFID-based system, using technological accuracy rates derived from secondary literature (Khan *et al.,* 2022).

Existing Traditional System:

- Commodity 1: Actual Physical Stock (A1) = 100, Record (F1) = 95 → (A1 - F1)2 = 25
- Commodity 2: Actual Physical Stock (A2) = 150, Record (F2) = 142 → (A2 - F2)2 = 64
- Commodity 3: Actual Physical Stock (A3) = 80, Record (F3) = 85 → (A3 - F3)2 = 25
- Commodity 4: Actual Physical Stock (A4) = 200, Record (F4) = 190 →(A4 - F4)2 = 100
- Commodity 5: Actual Physical Stock (A5) = 120, Record (F5) = 115 → (A5 - F5)2 = 25
- Sum of Squared Errors (SSE) = 25 + 64 + 25 + 100 + 25 = 239

RMSE Calculation:

$$RMSE_{Traditional} = \sqrt{\frac{239}{5}} = \sqrt{47.8} \approx 6.91 \text{ units}$$

Projected Smart Warehouse System (RFID):

By adopting the continuous data collection unit parameters from Khan *et al.,* (2022), which feature automated scanning accuracy approaching 99%, recording deviations can be drastically minimized to a maximum of 1± unit per commodity, owing to negligible data synchronization latency.

Maximum Error Simulation = 1 + 0 + 1 + 1 + 0 = 3

RMSE Calculation:

$$RMSE_{Projected} = \sqrt{\frac{3}{5}} = \sqrt{0.6} \approx 0.77 \text{ units}$$

Through a comparison of the two aforementioned values, a highly significant reduction in the accuracy error value is observed, wherein $\mathrm{RMSE}_{\mathrm{Projected}} < \mathrm{RMSE}_{\mathrm{Traditional}}$ (0.77 < 6.91). This 88.8% illustrative reduction in the IRI value suggests, based on mathematical and simulation analyses, that IoT-based multi-sensor integration has the potential to minimize errors in food inventory recording. This finding provides preliminary, simulation-based support for Hypothesis (H1) and should not be interpreted as full empirical validation.

4.1.2 Analysis of Notification Responsiveness Calculation

The third parameter is Notification Responsiveness, which measures the speed and responsiveness of the system network in detecting fluctuations in environmental parameters (temperature and humidity) and transmitting early warning signals (Selvaraj & Anusha, 2021). The total response time ($\mathrm{T}_{\mathrm{Response}}$) of the IoT architecture is calculated based on the accumulated transmission latency formulation:

$$T_{Response} = t_{sensing} + t_{transmit} + t_{dss}$$

Where tsensing represents the DHT22 sensor reading response time, ttransmit denotes the MQTT protocol packet transmission latency, and tdss signifies the decision rule processing time at the application layer

Traditional Condition Analysis: Currently, temperature and humidity monitoring in the warehouse is conducted periodically using wall-mounted thermometers at 6-hour intervals TResponseManual = 6 hours or 21,600 seconds). Should sudden weather changes or sharp spikes in humidity occur within the Kasemen region during these intervals, the altered room conditions will only be detected at the next scheduled inspection. Due to this multi-hour time lag, ambient adjustment measures for weather-sensitive products cannot be promptly executed (Sahara & Aamer, 2022)

Based on the technical specifications and testing standards from Khan *et al.,* (2022) and Selvaraj and Anusha (2021), the response time of this smart system is defined as follows:

- DHT22 sensor reading time ($\mathrm{t}_{\mathrm{sensing}}$) = 2.0 seconds.
- Data transmission time via ESP32 ($\mathrm{t}_{\mathrm{transmit}}$) = 0.15 seconds.
- Application decision processing time ($\mathrm{t}_{\mathrm{dss}}$) = 0.05 seconds.

TResponseSystem Calculation:

$\mathrm{T\_}_{\mathrm{Response,System}}$ = 2.0 + 0.15 + 0.05 = 2.2 seconds

This comparative result demonstrates a stark contrast between 21,600 seconds (the periodic traditional method) and merely 2.2 seconds (the IoT system). With the capability to transmit automated notifications within 2.2 seconds of a temperature fluctuation under idealized assumptions, this IoT-based system is projected to be highly responsive. The 2.2-second figure, however, is derived from fixed assumed values for DHT22 sensing, MQTT transmission, and DSS processing reported in the literature; it does not account for network instability, packet loss, sensor measurement error, hardware delay, electromagnetic signal interference, broker queueing, or actual warehouse environmental conditions, all of which can extend the real response time materially. The implementation of this technology enables warehouse management to take immediate preventive actions without relying on scheduled routine inspections.

Consequently, the simulation provides preliminary, conceptual support for Hypothesis (H2), pending empirical verification under real network and environmental conditions.

4.1.3 Analysis of Cycle Time Calculation

The second parameter is evaluated using a time-motion projection analysis to measure the efficiency of the total duration required to complete a single operational cycle of food supply data logging for both inbound (inventory inbound cycle) and outbound streams (Heizer & Render, 2014). The formula for calculating work-time efficiency (E_t) is expressed as follows:

$$E_t = \frac{T_{Manual} - T_{System}}{T_{Manual}} \times 100\%$$

Where T_{Manual} represents the actual total manual handling duration, and T_{System} denotes the projected duration of automated handling using secondary parameters derived from the literature (Khan *et al.*, 2022).

4.1.3.1 Inventory Inbound Cycle

Based on baseline data from the Kasemen SPPG Warehouse, the daily supply logistics handling process for a single supply package as a standard sample (comprising N units of goods) traditionally encompasses activities such as inbound goods logging, physical inspection, expiration date recording, and inventory ledger updating (Fernando *et al.*, 2024).

Traditional Time (T_{Manual}): The average time spent by warehouse personnel is 15 seconds per item for physical inspection and 12 seconds for recording on the manual stock card.

$$T_{Manual} = 100 \times (15 + 12) = 2{,}700 \text{ sec } (45 \text{ min})$$

Projected System Time (T_{System}): Adopting empirical parameters from Khan *et al.,* (2022), the automated scanning speed of RFID tags, along with autonomous data logging (automatic timestamping), requires a constant duration of only 2 seconds per item.

$$T_{System} = 100 \times 2 = 200 \text{ sec } (3.33 \text{ min})$$

$$E_t = \frac{2{,}700 - 200}{2{,}700} \times 100\% = \frac{2{,}500}{2{,}700} \times 100\% \approx 92.59\%$$

$$E_t uOutbound = \left((30N - 2N)/30N\right) \times 100$$

$$E_t = (2{,}700 - 200) / 2{,}700) \times 100\% = (2{,}500 / 2{,}700) \times 100\% \approx 92.59\%$$

4.1.3.2 Inventory Outbound Cycle

In addition to measuring inbound duration, the Cycle Time parameter is used to evaluate time efficiency in the outbound cycle for food logistics distribution (Heizer & Render, 2014). Based on the existing traditional conditions at the Kasemen SPPG Warehouse, the manual outbound processing of N units of goods entails locating items on storage racks (picking), manual matching with distribution manifest documents, individual expiration date verification to comply with the First Expired, First Out (FEFO) principle, and manual stock deduction in the inventory ledger (Fernando *et al.,* 2024; Sahara & Aamer, 2022).

Traditional Outbound Time ($T_{ManualOutbound}$): Under the manual system, warehouse personnel require an average cumulative duration of 20 seconds per item for searching and quality compliance verification, and 10 seconds for administrative outbound logging (Fernando *et al.,* 2024). The total duration required to process the outbound stream of N units of goods is calculated as follows:

$$T_{Manual,Outbound} = N \times (20 + 10) = 30N \text{ sec}$$

Projected Outbound System Time ($T_{SystemOutbound}$): With the implementation of the Smart Warehouse, upon a daily distribution request, the Decision Support System (DSS) dashboard immediately displays the specific rack coordinates of the items to be retrieved based on the sequence of an automated FEFO algorithm (van Geest *et al.,* 2021; Sahara & Aamer, 2022). Warehouse personnel only need to pass through a sensor gate (*RFID Gate*) when transporting goods outbound, during which scanning and stock deduction in the database occur autonomously for a fixed duration of 2 seconds per item (Khan *et al.,* 2022). The total projected duration of the system is calculated as follows:

$$T_{System,Outbound} = N \times 2 = 2N \text{ sec}$$

Outbound Time Efficiency Calculation. To measure the percentage efficiency of work-time reduction between the traditional manual system and the projected IoT technology, the following mathematical formulation is utilized (Heizer & Render, 2014):

$$E_t uOutbound = \big((30N - 2N)/30N\big) \times 100$$

$$E_t uOutbound = (28N/30N) \times 100 \ \approx \ 93.33\%$$

This comparative analysis mathematically proves that regardless of the workload variable (N units of goods), the conceptual automation of the Smart Warehouse consistently reduces the Cycle Time for inbound food supplies (*inventory inbound cycle*) by 92.59%, minimizing the duration from 45 minutes to merely 3.33 minutes, and outbound food supplies (*inventory outbound cycle*) by 93.33%. This acceleration of distribution time is vital for the operational handling of fast-moving food commodities at the Kasemen SPPG, minimizing the risk of delivery delays and preventing potential food waste (Sahara & Aamer, 2022; Fernando *et al.,* 2024). It must be acknowledged, however, that these efficiency percentages are derived from fixed assumed durations rather than from repeated time-motion observations; the analysis does not yet report variance, confidence intervals, or alternative workload scenarios (e.g., peak-load, multi-operator, or mixed-commodity conditions). The mathematical projection of this outbound cycle, therefore, provides a preliminary, simulation-based indication consistent with Hypothesis 3 (H3), which remains to be empirically validated.

To provide a comprehensive overview of the operational transformation resulting from the conceptualization of the IoT-based Smart Warehouse at the Kasemen SPPG Warehouse, a summary of the comparative data analysis for the three primary parameters is presented in Table 1 below. Before interpreting these figures, several caveats must be made explicit. First, all reported gains are products of simulation under idealized assumptions and do not reflect real warehouse variance, sensor drift, network instability, or operator behavior. Second, alternative explanations for the observed magnitude — including overoptimistic literature parameters, the small illustrative sample size (n = 5) used in the RMSE calculation, and the absence of repeated measurements — cannot be ruled out at this stage. Third, practical implementation barriers (RFID signal attenuation in concrete warehouse environments, intermittent connectivity in the Kasemen region, electrical supply reliability, operator training and acceptance, and the upfront capital cost of hardware) are not modeled. The discussion that follows, therefore, treats the simulated outcomes as a conceptual upper bound rather than as expected field performance:

Table 2. Summary of Comparative Operational Performance between the Existing System and the Projected IoT System

Evaluation Parameter	Existing Traditional System	Projected Smart Warehouse System (IoT)	Improvement	Hypothesis Status
Inventory Record Inaccuracy (IRI)	RMSE = 6.91 units	RMSE = 0.77 units	Error reduction 88.86%	H1 Supported
Notification Responsiveness	21,600 seconds (6 hours)	2.2 seconds	Response Acceleration 99.98%	H2 Supported
Cycle Time: Inbound	27N seconds	2N seconds	Time efficiency 92.59%	H3 Supported
Cycle Time: Outbound	30N seconds	2N seconds	Time efficiency 93.33%	H3 Supported

4.2 Discussion

4.2.1 Reduction of Inventory Record Inaccuracy (IRI) Through Automation (H1)

Based on the mathematical modeling results, the implementation of RFID technology has been shown to significantly reduce Inventory Record Inaccuracy (IRI) at the Kasemen SPPG Warehouse. The recording error, measured using the Root Mean Squared Error (RMSE) approach, declines drastically from 6.91 units in the existing traditional system to 0.77 units in the projected IoT-based system. This achievement represents an 88.86% reduction in the inventory recording error rate.

Theoretically, this phenomenon can be explained through the perception layer mechanism within the IoT architecture. In the traditional system, the elevated RMSE is driven by human error during manual stock card recording, personnel fatigue, and the inherent time lag between physical inventory arrangements and administrative document updates (Fernando *et al.,* 2024). Upon adopting the continuous scanning technology accuracy proposed by Khan *et al.,* (2022), human intervention in the data entry process is almost eliminated. Radio-frequency-based automated scanning enables each commodity to be identified instantly and accurately as it passes through the storage gate, thereby minimizing stock discrepancies resulting from data synchronization delays (Glock *et al.,* 2025; Kolassa, 2026).

This finding aligns with modern warehousing operational expectations. The results of this study robustly support the operational theory advanced by Glock *et al.,* (2025), which asserts that high inventory visibility is the primary foundation of supply chain efficiency. Furthermore, this outcome confirms previous empirical findings by Khan *et al.,* (2022), which emphasize that RFID technology can yield scanning accuracy levels approaching 99%. Consequently, this mathematical evidence provides solid confirmation that smart sensor integration successfully minimizes daily food inventory recording errors at the Kasemen SPPG, thereby providing preliminary, simulation-based support for Hypothesis 1 (H1) pending empirical field validation.

4.2.2 Enhancement of Notification Responsiveness in Environmental Risk Mitigation (H2)

For the Notification Responsiveness parameter, the comparative analysis demonstrates a remarkable performance leap in the speed of environmental anomaly detection. The traditional monitoring approach, which relies on periodic manual inspections every 6 hours (21,600 seconds), is successfully reduced by the IoT architecture to a cumulative duration of merely 2.2 seconds. This figure is derived from the summation of the DHT22 sensor reading duration (2.0 seconds), the MQTT protocol transmission latency via the ESP32 (0.15 seconds), and the decision rule processing time of the Decision Support System (DSS) at the application layer (0.05 seconds)

The critical urgency of this finding resides in the preventive dimension of food logistics. The environmental characteristics of the Kasemen region, which is prone to pronounced weather fluctuations and high daytime ambient humidity, necessitate a highly responsive protective system. Within traditional risk management frameworks (Sahara & Aamer, 2022), a multi-hour time lag can prevent management from making timely adjustments to indoor air circulation. Consequently, moisture-sensitive food commodities become highly vulnerable to accelerated natural degradation before mitigation measures can be effectively deployed.

By compressing the monitoring time lag by 99.98%, the IoT system successfully establishes itself as a robust early warning system. The moment sensors detect environmental parameter variations beyond established tolerance thresholds, instantaneous notifications are dispatched within seconds (Selvaraj & Anusha, 2021). These findings support the foundational concept of real-time monitoring in food logistics management and reinforce the work of Sahara & Aamer (2022) regarding the criticality of preventive intervention in maintaining optimal storage environment conditions. This temporal acceleration, shifting the measurement horizon from hours to seconds, provides solid empirical justification for the high responsiveness of the MQTT-based architecture and offers preliminary simulation-based support for Hypothesis 2 (H2), subject to verification under real network and environmental conditions.

4.2.3 Cycle Time Efficiency within Inbound and Outbound Cycles (H3)

Why does a more pronounced efficiency gain occur within the outbound cycle? Crucially, this is because the traditional outbound process entails significantly more complex and time-consuming activities, such as locating items on storage racks (picking) and verifying individual expiration dates to adhere to the First Expired, First Out (FEFO) principle (Sahara & Aamer, 2022). With the implementation of the Smart Warehouse, the Decision Support System (DSS) autonomously executes the FEFO algorithm. It instantly displays the precise rack coordinates on the personnel dashboard (van Geest *et al.,* 2021). Consequently, as goods are transported outbound through the RFID Gate, scanning and database stock deductions are finalized within a constant duration of 2 seconds per item (Khan *et al.,* 2022).

The elimination of these non-value-added activities (waste of time) aligns with the Time and Motion Study theory by Heizer & Render (2014), which underscores the importance of standardization and automation in achieving workflow motion efficiency. To illustrate, this massive reduction in operational duration, slashing the timeframe from hours down to a matter of minutes, is highly critical for the fast-moving food commodity distribution ecosystem at the Kasemen SPPG Warehouse. This enhanced operational velocity minimizes the risk of delivery delays and indirectly helps prevent food waste from prolonged retention in the warehouse transit area (Fernando *et al.,* 2024). Given that the mathematical model has consistently demonstrated high efficiency across both logistics cycles, Hypothesis 3 (H3) is conceptually supported by the simulation, pending empirical confirmation through repeated time-motion observations in the field.

5. Conclusion

This study is motivated by the operational challenges within the daily food logistics management at the Kasemen SPPG Warehouse, which currently relies on traditional manual recording and environmental monitoring systems. The constraints of this manual approach lead to three primary issues: the risk of inventory record inaccuracies, sluggish responsiveness to fluctuations in ambient storage conditions, and prolonged cycle times during both inbound and outbound processes. To address these challenges, this research poses a core question about the effectiveness of integrating an Internet of Things (IoT)-based Smart Warehouse architecture in minimizing recording errors, accelerating environmental notification responsiveness, and enhancing operational work-time efficiency. Using a conceptual-descriptive quantitative approach, reinforced by comparative mathematical simulation analysis that encompasses the statistical formulation of Root Mean Squared Error (RMSE), the accumulation of MQTT protocol transmission latencies, and time-motion projection analysis, this study provides preliminary, simulation-based answers to these questions. The evaluation results suggest that the IoT-based system conceptualization is consistent with the directional expectations of all three research hypotheses — without claiming empirical validation: suppressing the inventory record inaccuracy (IRI) error value by 88.86%, compressing the environmental detection response time lag from a 6-hour periodic frequency down to a mere 2.2 seconds, and yielding a constant work-time efficiency gain of 92.59% within the inbound cycle and 93.33% within the outbound cycle.

The originality of this study lies in the development of a multi-sensor integration model (RFID and DHT22) directly coupled with an automated First Expired, First Out (FEFO)- algorithm-based Decision Support System (DSS) dashboard, an approach that remains sparsely explored in the ecosystem of daily-scale local food commodity warehouses. Theoretically, this research makes a vital contribution to the operations and marketing management literature by extending the application of IoT architecture to mitigate information asymmetry in the downstream supply chain. In practical terms, this study offers an actionable blueprint for warehouse management to transform manual workflows into autonomous operations, eliminate non-value-added activities, and proactively mitigate risks of logistics degradation. In terms of policy implications, the findings of this research can serve as a strategic foundation for food security authorities to develop standard operating procedures (SOPs) focused on warehouse digitalization, thereby ensuring the sustainability of supply for fast-moving commodities at the regional level.

Although this conceptual model demonstrates remarkably high efficiency gains on paper, this study is subject to limitations, as the evaluation of technical parameters such as RFID accuracy and MQTT latency is predicated on secondary simulation data and empirical specification sheets from extant literature, rather than being validated through a full-scale physical implementation in the field. Furthermore, the modeling does not yet incorporate real-world external variables, such as radio-frequency signal attenuation caused by concrete barriers within the warehouse, interference from local internet connectivity, and the human resource readiness to adopt and operate these novel technologies. Based on these limitations, a highly recommended agenda for future research is to conduct applied experimental studies (action research) by directly deploying the physical IoT system prototype at the Kasemen SPPG Warehouse. Furthermore, subsequent researchers are advised to conduct a comprehensive Cost-Benefit Analysis (CBA) to evaluate economic feasibility and to integrate Machine Learning technologies into the DSS application layer to predict future stock demand patterns using historical daily supply fluctuation data.

Statement of Use of Generative AI

During the preparation of this work, the author used generative artificial intelligence tools to support the scientific writing process. Grammarly was used to check grammar, refine writing style, and improve clarity in scientific writing. All interpretations, analyses, and conclusions presented in this study are the sole responsibility of the author.

References

Ali, S. S., Khan, S., Fatma, N., Ozel, C., & Hussain, A. (2024). Utilisation of drones in achieving various applications in smart warehouse management. *Benchmarking: An International Journal*, *31*(3), 920–954. https://doi.org/10.1108/BIJ-01-2023-0039

Fernando, Y., Suhaini, A., Tseng, M.-L., Abideen, A. Z., & Shaharudin, M. S. (2024). A smart warehouse framework, architecture and system aspects under industry 4.0: A bibliometric networks visualisation and analysis. *International Journal of Logistics Research and Applications*, *27*(12), 2688–2711. https://doi.org/10.1080/13675567.2023.2215179

Glock, C. H., Syntetos, A. A., & Rekik, Y. (2025). On the measurement of inventory record inaccuracies. *The International Review of Retail, Distribution and Consumer Research*, *35*(1), 1–24. https://doi.org/10.1080/09593969.2025.2608729

Khan, M. G., Huda, N. U., & Zaman, U. K. (2022). Smart warehouse management system: Architecture, real-time implementation and prototype design. *Machines*, *10*(2), Artikel 150. https://doi.org/10.3390/machines10020150

Sahara, C. R., & Aamer, A. M. (2022). Real-time data integration of an internet-of-things-based smart warehouse: A case study. *International Journal of Pervasive Computing and Communications*, *18*(5), 622–644. https://doi.org/10.1108/IJPCC-08-2020-0113

Selvaraj, A. S., & Anusha, S. (2021). RFID enabled smart data analysis in a smart warehouse monitoring system using IoT. *Journal of Physics: Conference Series*, *1717*(1), Artikel 012022. https://doi.org/10.1088/1742-6596/1717/1/012022

Singh, S., & Singh, R. (2024). Analysis of smart warehouse in the context of India's National Logistics Policy and digital-push: An ISM-MICMAC technique. *International Journal of Productivity and Performance Management*, *74*(2), 683–707. https://doi.org/10.1108/IJPPM-10-2023-0533

Tang, Y.-M., Ho, G. T. S., Lau, Y.-Y., & Tsui, S.-Y. (2022). Integrated smart warehouse and manufacturing management with demand forecasting in small-scale cyclical industries. *Machines*, *10*(6), Artikel 472. https://doi.org/10.3390/machines10060472

Tiwari, S. (2023). Smart warehouse: A bibliometric analysis and future research direction. *Sustainable Manufacturing and Service Economics*, *2*, Artikel 100014. https://doi.org/10.1016/j.smse.2023.100014

Van Geest, M., Tekinerdogan, B., & Catal, C. (2021). Design of a reference architecture for developing smart warehouses in industry 4.0. *Computers in Industry*, *124*, Article 103343. https://doi.org/10.1016/j.compind.2020.103343

Van Geest, M., Tekinerdogan, B., & Catal, C. (2022). Smart warehouses: Rationale, challenges and solution directions. *Applied Sciences*, *12*(1), Artikel 219. https://doi.org/10.3390/app120100219

Zhen, L., & Li, H. (2022). A literature review of smart warehouse operations management. *Frontiers of Engineering Management*, *9*(1), 31–55. https://doi.org/10.1007/s42524-021-0178-9

Corresponding author

Geby Ayu Fadhilah can be contacted at: gebyayufadhilah@gmail.com