Implementation of IoT & AI Technology for Quality Enhancement in Real-time Pharmaceutical Storage Monitoring

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***Abstract*—With the development of Artificial Intelligence (AI), scientists have been focusing on utilizing real-time pharmaceutical monitoring for multiple purposes. One of the main sectors benefiting from this is minimizing wastage. In this study, we introduce the ability to monitor pharmaceutical products through the integration of AI and the Internet of Things (IoT) to achieve real-time product management and waste reduction. The study introduces smart sensors that monitor the temperature and humidity of the medication in pharmacy cold storage. The system involves a decision mechanism to check for abnormalities. If regular conditions are recorded, the storage process is continued normally, and data are auto logged. However, if abnormalities are detected, the AI-assisted controller executes a bounded automatic adjustment of cooling parameters while simultaneously notifying the supervisor; all events are recorded for audit. In addition, we model the As-Is/To-Be processes using Business Process Model Notation (BPMN) and evaluate a 30-day Bizagi simulation for pharmacy cold storage. KPIs indicate substantial gains such as faster detection, alerting, corrective response, and improved auto-logging coverage. These results support the feasibility of the AI and IoT approach for improving real-time pharmaceutical monitoring and reducing potential wastage.**

***Keywords*—real-time monitoring, pharmaceutical, storage monitoring, Internet of Things (IoT), Artificial Intelligence (AI)**

I. Introduction

The Internet of Things (IoT) is a technology used to monitor systems remotely and at scale, enabling stakeholders to monitor products in real-time. The healthcare industry is one of the sectors that best suited to integrate IoT and AI technologies, which are key drivers for improving quality of monitoring and enhancing patient safety. This study focuses on pharmacy cold storage (2–8 C), where timely detection and response are essential to protect medicine integrity and reduce wastage. Because patient safety is paramount and medicine quality underpins effective care, reliable monitoring and proper storage in pharmacy cold storage are essential.

This study presents a crucial point about life-saving drugs and quality enhancement in pharmaceutical storage monitoring, and the potential of IoT and AI based solutions for the smart cold chain. The general objective of this study is to develop a simulation-based IoT-AI framework for improving real-time monitoring and quality control in pharmaceutical cold storage. The specific objectives are to: (1) model the current manual storage process and identify its operational weaknesses; (2) determine the principal causes of delays and abnormal storage conditions; (3) redesign the process using IoT sensors and AI-assisted decision support; (4) evaluate the proposed redesign through simulation-based KPI comparison; and (5) assess the feasibility of the proposed framework for improving responsiveness, data logging, and storage quality.

There are various factors that affect the stability environmental conditions related to medicines quality, especially outside hospitals. Monitoring systems are crucial to safeguard efficacy and reduce health risks. Recent advancements include the integration of commercial and custom-designed sensor nodes that allow multi-variable environmental monitoring.

The pharmaceutical products are sensitive: when exposed to unsuitable environmental conditions (temperature, humidity, light), medicines may deteriorate. There are specific issues faced pharmaceutical monitored manually, with reading recorded several times per day. A limitation of traditional monitoring meaning stored data can only be accessed once after device retrieval and analysis, preventing real-time corrective actions. When temperature changes go undetected, corrective action is delayed, which in turn leads to medicine spoilage and potential waste. This research aims to enhance real-time monitoring and corrective action by using IoT smart sensors within monitor, alarm and notification systems, provide comprehensive monitoring 24/7, generate alerts, store log files, and build automatic monthly reports.

Moreover, this technology will be saving time, increase efficiency, enhance features and architecture [1]. Although allowing proactive detection of deviations from ideal conditions, decreasing risks of products deterioration [2].

II. Literature Review

Recent studies have shown that IoT technologies can improve pharmaceutical storage monitoring by enabling continuous sensing, remote supervision, and timely alerts. These systems are commonly used to track temperature, humidity, and other environmental variables that affect medication quality. Prior work has demonstrated that connected monitoring devices can improve visibility across storage and transportation processes, while also supporting better traceability and faster response to deviations. However, many existing IoT solutions focus mainly on sensing and notification, with less attention given to process redesign or decision support in cold-storage operations.

Digital twin research has also contributed to pharmaceutical operations by allowing researchers to model, simulate, and evaluate complex processes before

implementation. In healthcare and pharmaceutical supply chains, digital twins can support scenario testing, forecasting, and operational resilience. Even so, current studies often remain limited to specific facilities or supply chain contexts, and few combine digital modeling with direct improvements in cold-storage monitoring workflows. This creates a need for applied research that connects process analysis with operational redesign.

Artificial intelligence and machine learning have been widely applied in pharmaceutical forecasting, inventory optimization, and logistics prediction. Studies have reported the use of methods such as random forest, gradient boosting, long short-term memory networks, and other predictive models to improve operational decisions. These approaches are valuable when sufficient structured data are available, but many of them are designed for forecasting rather than immediate environmental control. In real-time storage monitoring, the challenge is not only prediction but also rapid detection, alert generation, and corrective response.

Blockchain and traceability studies have further highlighted the importance of data integrity, serialization, and supply chain visibility in pharmaceutical systems. These technologies can strengthen trust and accountability, but they do not directly solve the problem of real-time temperature and humidity control in storage environments. Likewise, security and quality assurance research emphasizes the need for audit trails, access control, and reliable data handling in connected healthcare systems. Taken together, the literature suggests that an integrated framework combining IoT monitoring, AI-based support, and process redesign may offer greater practical value for pharmacy cold storage than isolated technologies used independently. In the following sub-sections, we provide more details.

A. IoT for Storage Monitoring

Recent studies have shown that Internet of Things (IoT) solutions can improve pharmaceutical storage oversight by enabling continuous sensing, remote supervision, and timely alerts [1]. For example, the QChainMED framework integrates multiple sensors to monitor temperature, humidity, light exposure, and mechanical stress during both storage and transportation, thereby supporting safer medication handling and improved patient protection. Another study implemented a Wi-Fi-based sensor system for real-time temperature and humidity monitoring in a drug storage room, demonstrating the practical value of remote environmental supervision while also noting limitations in cooling performance and component selection [2].

IoT-based smart pharmaceutical packaging has also been proposed to enhance integrity and traceability across the storage and distribution chain. These studies collectively indicate that IoT can strengthen monitoring coverage, but they also reveal recurring concerns related to system complexity, calibration, and data security. However, many existing solutions emphasize sensing and alerting only, while fewer studies combine real-time monitoring with process redesign and automated decision support in a pharmacy cold-storage context [3].

B. Digital Twin Applications

Digital twin technology has emerged as a promising approach for representing and analyzing pharmaceutical operations through the integration of simulation and visualization [4]. Prior work has shown that digital twins can improve resource forecasting, enhance responsiveness to supply disruptions, and support more informed operational decisions in pharmaceutical supply chains [5]. Studies also suggest that when digital twins are combined with IoT and predictive analytics, they can provide scenario testing and resilience evaluation for healthcare logistics and manufacturing [6].

Despite these benefits, the literature also reports limitations such as high implementation cost, restricted scalability, and data integration challenges. In addition, several studies remain context-specific, focusing on particular products, facilities, or geographic settings, which limits generalizability. These observations suggest a need for more applied work that links process modeling with practical monitoring improvement in pharmaceutical storage environments [7].

C. AI and ML for Forecasting and Operations

Artificial intelligence and machine learning have been widely applied to forecasting, inventory optimization, and logistics prediction in pharmaceutical and hospital pharmacy contexts [8]. Previous studies have used models such as long short-term memory networks, random forest, gradient boosting, and deep reinforcement learning to predict shortages, optimize stock levels, and improve shipment time estimation [9]. Reported outcomes show improved predictive accuracy and better performance than traditional baseline methods in several operational settings [10].

However, most of these studies focus on forecasting or inventory planning rather than direct real-time storage control [11]. In addition, some models depend on large, structured datasets that may not be available in all pharmacy environments [12]. This indicates a gap between predictive analytics and operational implementation, especially in cold-storage monitoring where immediate detection and corrective action are critical [13].

D. Blockchain and Traceability

Blockchain-based solutions have been introduced to improve traceability, integrity, and anti-counterfeiting capabilities in pharmaceutical supply chains. Prior studies have proposed frameworks that serialize products, assign unique identifiers, and use smart contracts to record product movement and reduce tampering risks. These approaches enhance trust and transparency across distribution networks and support end-to-end visibility [14].

Nevertheless, the literature also notes challenges related to scalability, interoperability, and implementation complexity. While blockchain can strengthen traceability, it does not directly solve the problem of real-time environmental control in storage facilities. Therefore, blockchain should be viewed as a complementary technology rather than a substitute for monitoring and decision-support systems [15].

E. Security and Data Integrity

Security and data integrity are essential requirements in pharmaceutical digital transformation, particularly when sensitive operational data are collected and transmitted through connected systems. Prior research has highlighted zero-trust architecture and electronic data integrity controls

as effective ways to reduce cyber risk and prevent tampering or loss. These studies emphasize the importance of secure monitoring infrastructures that preserve both reliability and compliance [16].

At the same time, security requirements increase the design complexity of IoT-enabled healthcare systems. As a result, monitoring solutions should be developed with attention to authentication, access control, audit trails, and secure data handling. This is especially important when the monitoring system is intended to support quality assurance and decision-making in pharmaceutical storage [17].

F. Regulatory and Quality Assurance

The literature on pharmaceutical quality assurance consistently emphasizes compliance, traceability, and process control as core requirements for protecting product integrity. Recent studies argue that AI, automation, and digital technologies can improve responsiveness and support regulatory adherence, especially in complex supply chains. However, several reviews also point out that practical case studies remain limited and that stronger alignment between technology design and regulatory requirements is needed.

Taken together, the literature shows that IoT, AI, digital twins, blockchain, and data-security mechanisms each contribute to improving pharmaceutical operations. However, fewer studies integrate these ideas into a single framework for real-time cold storage monitoring and process redesign. This gap motivates the present study [18].

III. Methodology

The methodology used in this research is based on the business process methodology in Fig. 1 which consists of the following stages.

A. Process Discovery

In this phase a comprehensive process discovery was done to model the manual pharmaceutical storage monitoring Fig. 2 shows a model for As Is Business Process.

B. Process Analysis

The As-Is process was modeled by documenting the current manual workflow used in pharmaceutical cold storage, beginning with the receipt of medicines and continuing through storage, manual inspection, recording in logbooks, detection of abnormalities, supervisor notification, and corrective action. This process was mapped as a business process model to reflect the actual operational sequence observed in the storage environment. The model was intended to represent the current state of work as faithfully as possible before redesigning it.

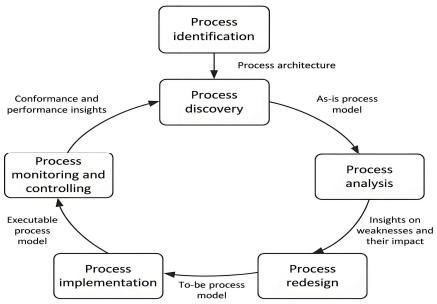

Fig. 1. BPM process methodolgy.

Process times were measured using the time required to complete each activity in the workflow. These included cycle time, detection time, alert latency, corrective action time, and data logging time. In the As-Is model, these values were based on the timing of manual activities and recorded process delays, while in the To-Be model they were based on the expected performance of the proposed automated workflow. The same KPI definitions were used in both models to ensure comparability.

The number of simulated events should be stated explicitly in the manuscript. If the simulation was run for a 30-day period in Bizagi, then the text should say that the process was simulated over 30 days and that the number of events reflected the modeled process instances generated during that period. If a fixed number of cases was used, that number should be reported directly. The manuscript should avoid leaving this unspecified, because it affects the interpretability of the results.

Fig. 1 depicts the different qualitative and quantitative analysis methods were carried to analyze the causes of out-of-range conditions in Pharmaceutical cold storage.

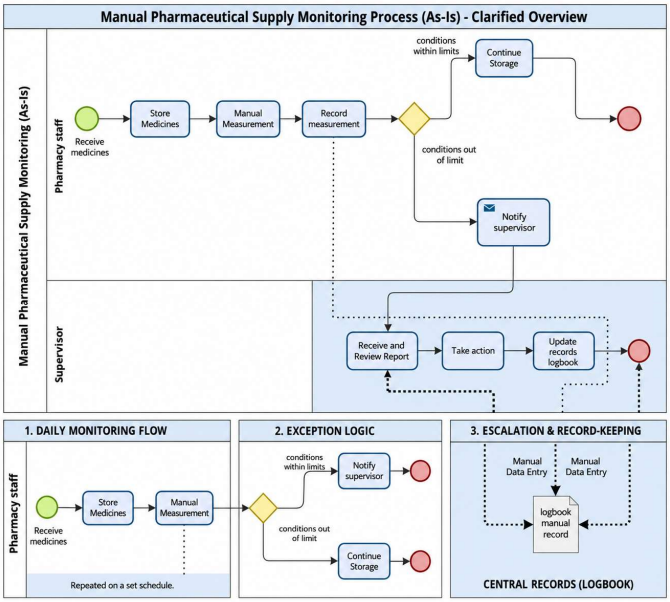

Fig. 2. As is business process model.

The Bizagi assumptions included a stable process environment, predefined task durations, fixed routing rules, and consistent response behavior for staff and automated actions. The simulation assumed that the process followed the modeled sequence without external disruptions beyond those represented in the scenario. It also assumed that the proposed monitoring system could detect abnormal conditions, generate alerts, and trigger corrective responses according to the defined workflow logic.

1) Qualitative analysis

a) Cause-effect (fishbone)

The fishbone diagram depicts the root causes of out-of-range conditions in manual pharmaceutical storage Fig. 3. The primary causes are delayed detection and action of abnormal conditions, which leads to medicines elimination. The analysis categorizes the causes into 6 groups: Man, Method, Measurement, Material, Machine, and Environment.

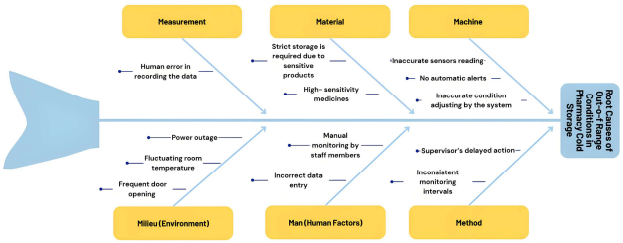

Fig. 3. Cause-effect process (Fishbone) diagram.

b) SWOT analysis

SWOT analysis; Fig. 4; is utilized to assess the performance, competition, risk, and potential of the proposed solution.

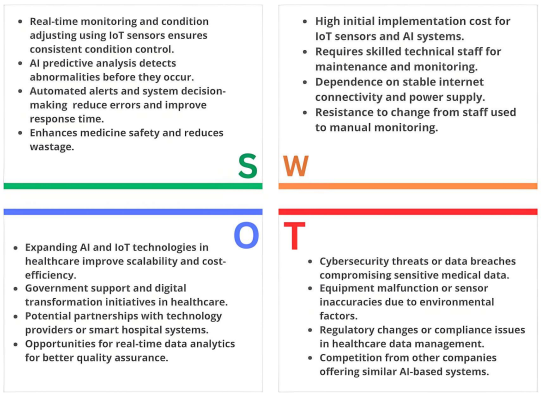

Fig. 4. SWOT analysis.

2) Quantitative analysis

a) Pareto analysis

The cumulative total is the process of adding numbers in succession, each time adding a new value to the pervious total. The goal is to see how values increase over time or as new factors are added as shown in Fig. 5. For example, in our topic we highlighted the 5 causes that effect in detection time, finding out the top 3 causes, Notification latency (30, 37.5%), Reading delay (20, 25.0%), and Processing queue (15, 18.75%), together account for 81.25%.

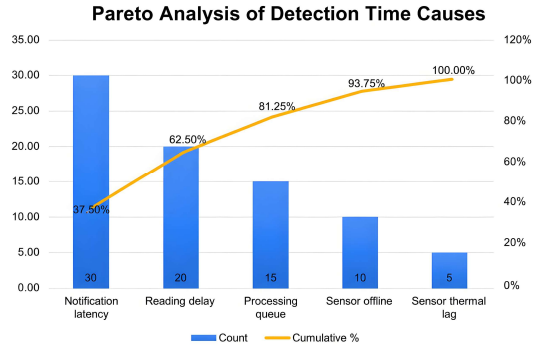

Fig. 5. Process pareto diagram.

Table 1 summarizes the Pareto analysis used to identify the main causes of delayed detection in the manual cold-storage process. The results show that notification latency is the largest contributor, followed by reading delay and processing queue, while sensor offline and sensor thermal lag account for smaller shares of the total problem. Together, the top three causes represent 81.25% of the detected delay-related issues, confirming that a limited number of recurring factors are responsible for most of the inefficiency. This finding supports the use of the 80/20 principle and justifies focusing the redesign on faster notifications, quicker readings, and reduced processing delays. Accordingly, Table 1 provides the evidence base for prioritizing the process improvements implemented in the proposed To-Be model. According to table 1, the 80/20 rule, the top three causes account for 81.25 are Notification latency, reading delay, and Processing queue contributes 80% of the causes of late detection, so they are our primary focus.

Table 1. Process pareto diagram

Causes (Affecting Detection Time)	Count.	Percent %	Cumulative %	80/20 Rule
Notification latency	30	37.50%	37.50%	80%
Reading delay	20	25.00%	62.50%	80%
Processing queue	15	18.75%	81.25%	80%
Sensor offline	10	12.50%	93.75%	80%
Sensor thermal lag	5	6.25%	100.00%	80%

b) KPIs simulation comparision

KPIs comparison in Table 2 shows the efficiencies of each process to determine performance; as the monitored variables for simulation results in minutes for each task in the current As Is model. This information allows for comparison with the To Be model after AI optimization; as an evaluation criteria used in the simulation.

Table 2. KPIs and simulation time results

KPIs	As-is	To-be	Difference
Average Cycle Time	7 1min 24 s	12 min 6 s	59.3 min faster
Detection Time	40 min	10 s	39 min 50 s faster
Alerts Latency	20 min	1 min 40 s	18 min 20 s faster
Data logging	15 manual	10s Auto	14 min 50 s faster

C. Process Redesign and Implementation

The AI element is presented as a simulation-based decision-support component within the proposed IoT framework. The full process scenario after redesigning the model and creating a proposed model using the IoT & AI technology below in Fig. 6, the process starts with receiving medicines and storing them in the cold room under controlled conditions. The sensors continuously read temperature and humidity etc., and AI component analyzes the data for predicting out-of-range conditions before happening. After that, if the status is abnormal, the system notifies the supervisor and generates an alarm automatically and the IoT&AI system execute decision-making process to adjust conditions automatically. After corrective action rapidly and the system rechecks conditions before closing. Otherwise, if the status is normal, the system auto-logs data to the data store, then the process completes. In the To-Be model, the main changed parameters were the introduction of continuous IoT sensor monitoring, automated abnormality detection, real-time alert generation, faster supervisor notification, automatic or bounded corrective action, and auto-logging of data. These modifications reduced delays associated with manual inspection and manual data recording. As a result, the simulated process showed shorter cycle times and improved monitoring responsiveness.

The KPI values were computed by comparing the average or observed time for each activity in the As-Is model with the corresponding time in the To-Be model. The difference between the 2 values was then reported as the performance improvement. For example, cycle time improvement was calculated as the reduction in total process duration, while detection time and alert latency were measured as the difference in response intervals between manual and automated conditions. Data logging improvement was measured by comparing manual recording time with automatic logging time.

Importantly, these results should be described as simulation-based outcomes rather than experimental or clinical evidence. The study does not claim real-world deployment or patient-level validation. Instead, it demonstrates the feasibility of the proposed IoT-AI redesign under modeled conditions and provides a structured basis for future prototype implementation and field testing. It proposes an AI component as simulation-based decision-support element.

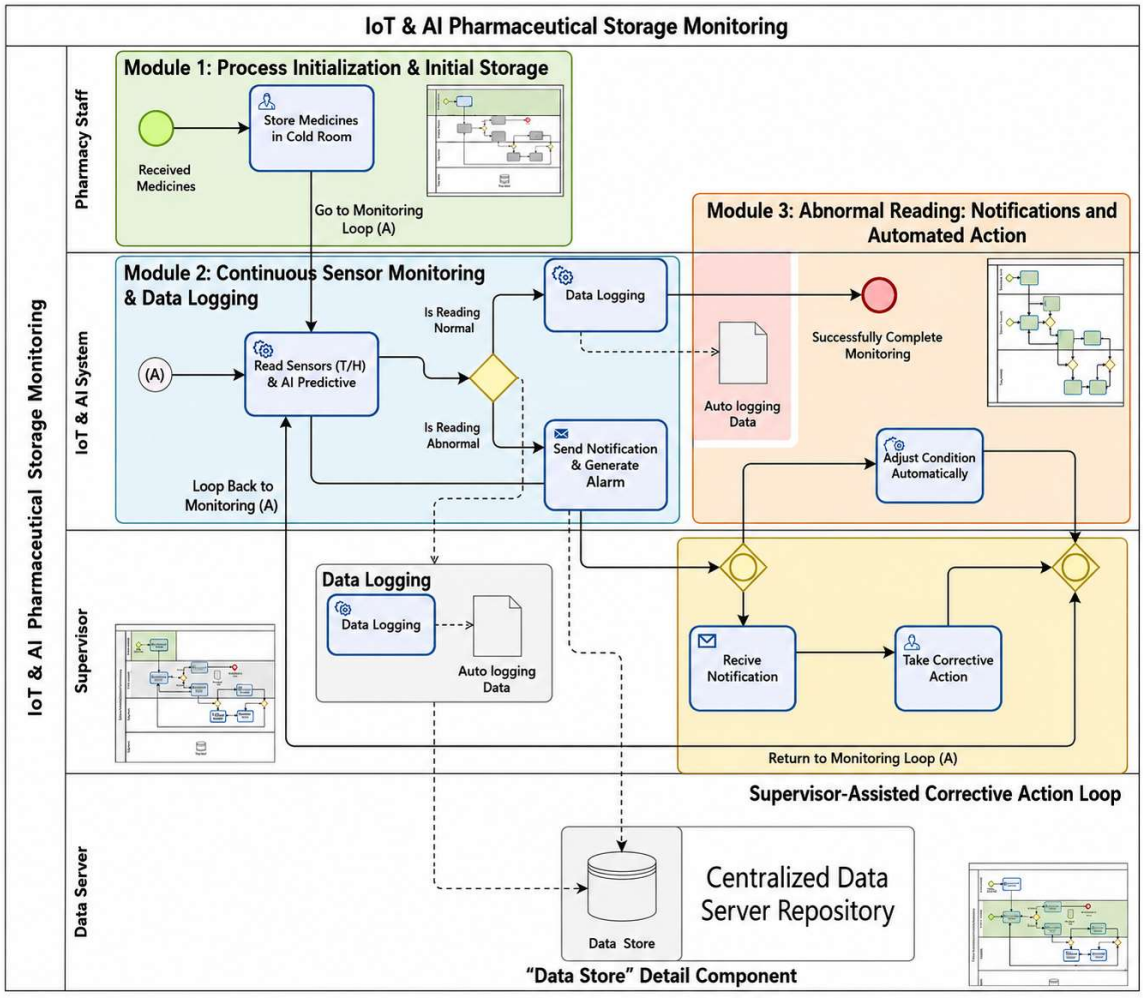

Fig. 6. To-be business model.

D. Process Monitoring and Controlling

1) TQM

We adapt a TQM approach to enhance To-Be model, we define the Critical-to-Quality (CTQ) requirements (Detection time, Alert Latency, Data logging), then establish SOPs for handling alerts, corrective actions, data integrity. Moreover, we deploy the IoT & AI that automatically adjusts cooling parameters while notifying the supervisor, with full audit logging. After that, checks the KPIs weekly and run a

monthly Pareto of incident causes, and ensure to do a KPIs after each cycle for continuous improvements.

Process capability analysis was conducted to assess whether the proposed To-Be process can operate within predefined performance limits under the simulation assumptions. In this study, the specification limits were defined according to the operational requirements of pharmaceutical cold-storage monitoring. The Upper Specification Limit (USL) represents the maximum acceptable response time for alert generation and corrective action, while the Lower Specification Limit (LSL) was set to zero because response time cannot be negative. These limits were used only as performance boundaries for the simulated process and not as experimental clinical thresholds.

The capability indices were computed from the simulated process mean and standard deviation using standard capability formulas. Specifically, C_p was used to measure the spread of the process relative to the specification width, whereas C_{pk} was used to evaluate both process variation and centering with respect to the specification limits. These indices therefore describe how well the modeled process fits within the defined performance range under common-cause variation. In this study, the reported capability values reflect the behavior of the simulated To-Be model and should be interpreted as indicative of potential performance rather than as evidence of real-world operational deployment.

Capability analysis is meaningful only when the process is sufficiently stable and the data are representative of the process being evaluated. Accordingly, the indices should be interpreted as valid for the simulated conditions used in this study, where the process parameters, routing logic, and task durations were predefined in the model. The results should not be generalized as empirical proof of field performance, because no live prototype or clinical implementation was tested. Instead, the capability analysis provides a structured statistical indication of how the proposed redesign may perform under the assumed simulation environment.

The process capability results are intended to illustrate the potential stability and responsiveness of the proposed To-Be model under the simulation assumptions

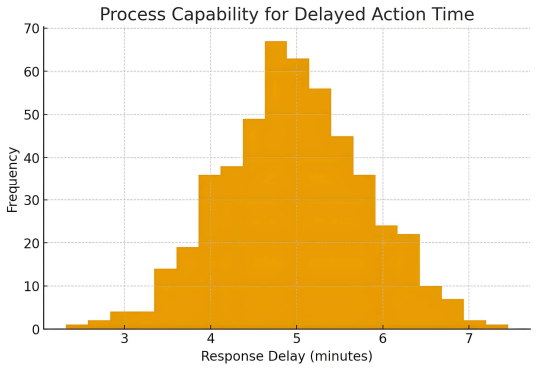

Fig. 7. Histogram of response delay time for process capability analysis.

A random sample of 400 detect time was generated with a mean of ≈ 20.1 min and a standard deviation of ≈ 3.25 min. The histogram and fitted normal distribution below show the process behavior relative to the specification limits.

Calculated capability indices are as follows:

$Cp = (USL–LSL)/(6\sigma) = 2.04$

$Cpl = (mean–LSL)/(3\sigma) = 2.04$

$Cpu = (USL–mean)/(3\sigma) = 2.04$

$Cpk = \min(Cpl, Cpu) \approx 2.04$

The capability results demonstrate that the to-be model IoT and AI monitoring system is highly capable and operates at 6 sigma. $Cp < 2.0$ indicates very low process variation. $Cpk < 2.0$ depicts the process is well- centered between the specification limits as shown in Fig. 7.

IV. Conclusion

This study addresses the problem of overcrowding in the emergency department and the associated delays and problems arising from manual registration and triage. It proposed an IoT- and AI-enabled framework for improving real-time pharmaceutical cold-storage monitoring through business process redesign and simulation-based evaluation. The main contribution is a structured To-Be process that combines continuous sensing, automated logging, alert generation, and bounded corrective response to support storage quality and reduce the risk of medicine wastage.

The simulation results suggest that the redesigned process can improve monitoring efficiency by reducing cycle time and shortening response delays compared with the manual As-Is process. The Pareto analysis further shows that a small number of recurring causes account for most incidents, indicating that targeted process improvement can produce meaningful operational gains. At the same time, the process capability analysis should be interpreted cautiously because it is based on modeled data and assumptions rather than a fully deployed operational system. In numbers, the results showed significant improvements and reductions in average time across all Key Performance Indicators (KPIs). Triage waiting time decreased by 90%, patient registration time upon arrival decreased by 50%, and examination time decreased by 21.9%.

The simulation results show that the redesigned process improves responsiveness by reducing detection and alert delays, strengthens documentation through more reliable data logging, and supports better storage quality by minimizing the time that medicines remain under abnormal conditions. Overall, the findings suggest that the proposed framework can enhance pharmacy cold-storage performance and provide a practical basis for future prototype development and real-world validation.

The study has several limitations. First, the AI component was modeled as part of the proposed architecture rather than validated through a deployed learning system. Second, the evaluation relied on simulation rather than live experimental or field data. Third, the results are specific to the modeled cold storage process and therefore should not be generalized without further testing.

Future research should implement a functioning AI prototype, collect real sensor data from operational pharmacy storage environments, and validate the framework under live conditions. Additional work should also expand the model to include larger datasets, stronger statistical validation, and broader integration with compliance, traceability, and decision-support mechanisms.

Conflict of Interest

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Sally Musattat and Taif Alsharif contributed equally to this work. Sally Musattat and Taif Alsharif were responsible for conceptualization, methodology, investigation, data curation, formal analysis, and writing the original draft of the manuscript. Salma Elhag contributed through supervision, methodology guidance, validation, writing—review and editing, and provided critical feedback throughout the research and manuscript preparation. All authors have read and approved the final version of the manuscript.

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