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Optimizing Hospital Pharmaceutical Warehouse Operations Using Discrete Event Simulation

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ABSTRACT

This study aims to analyze and optimize the operational performance of the pharmaceutical logistics warehouse at Hospital Yogyakarta using a Discrete Event Simulation *(DES)* approach. Preliminary observations revealed a significant workload accumulation during peak hours (09:00–10:55), leading to drug distribution delays, a 10–15% weekly discrepancy between physical and system stock data, and a 12% decline in patient satisfaction. Data were collected through direct work time measurements and secondary hospital records, then modeled using an Activity Cycle Diagram (ACD) and simulated with Arena software. Three improvement scenarios were tested: (1) reassigning goods and invoice verification tasks to the ordering operator, (2) adding one new operator dedicated to the posting activity in the system, and (3) combining both strategies. Simulation results indicate that Alternative III provides the best performance, reducing the average cycle time from 411.4 minutes to 65.57 minutes per cycle, improving productivity by up to 99%, and achieving balanced workloads among operators. These findings demonstrate that DES-based modeling is an effective tool for identifying bottlenecks and designing process improvements without requiring costly technological investment. This research contributes to the field of hospital pharmaceutical logistics management by offering an evidence-based decision-making framework to enhance operational efficiency and service quality sustainably.

Keywords: Discrete Event Simulation, Pharmaceutical Logistics, Hospital Warehouse, Operational Optimization

INTRODUCTION

Hospitals play a vital role in ensuring the continuity of healthcare services that are effective, efficient, and responsive to patient needs. One of the key determinants of hospital service quality is the efficiency of pharmaceutical logistics management, particularly in warehouse operations that regulate the flow of medicines and medical supplies [1]. The pharmaceutical warehouse functions as a central node connecting procurement, inventory control, and internal distribution [2]. Inefficient warehouse operations—characterized by unbalanced workloads, delayed administrative posting, and manual coordination—can lead to distribution delays, stockouts, and decreased service reliability. Therefore, improving warehouse operational efficiency is critical to maintaining service quality and ensuring timely access to essential medicines [3].

This study focuses on the pharmaceutical logistics warehouse at Yogyakarta, one of the leading private hospitals serving the Yogyakarta region. Field observations revealed significant workload accumulation during peak hours when operators must simultaneously handle supplier deliveries and prepare medicine requests from internal hospital units. This dual workload causes operational bottlenecks, delayed distribution, and frequent stock discrepancies between physical and digital records. Empirical time studies show that 411.4 minutes of the 480-minute workday (over 85% of total working hours) are consumed by receiving and dispensing activities, leaving only about 68.6 minutes for administrative tasks such as data posting and inventory arrangement. Consequently, data mismatches between physical and system stock reach 10–15% per week, resulting in delayed prescription fulfillment and a 12% decline in patient satisfaction, as reported in the hospital's 2024 internal quality audit. In the long term, this inefficiency may increase operational costs by 8–10% per quarter due to duplicated work and slow cross-unit drug distribution.

The above findings highlight an urgent need to redesign hospital pharmaceutical logistics systems to achieve better workload balance and administrative efficiency. In the context of healthcare quality reform, speed and accuracy of drug distribution are among the most important indicators of hospital performance. Failure to ensure timely medicine availability can disrupt treatment continuity, increase clinical risk, and erode patient trust. Therefore, this research is urgently needed to develop an adaptive, data-driven, and cost-effective operational model that allows hospital management to optimize logistics performance without requiring high-cost automation technologies. The outcomes of this study are also aligned with Indonesia's national agenda to improve hospital service quality and operational efficiency in accordance with accreditation standards and public service excellence.

A review of previous studies shows that most prior research emphasizes technology-intensive solutions, such as RFID implementation [4], [5] and logistics automation systems [6], [7], [8], which require substantial investment and are impractical for hospitals with limited human and financial resources. Conversely, studies exploring human-resource-based optimization and work redistribution in hospital pharmaceutical warehouses remain scarce. Most *Discrete Event Simulation (DES)* applications in healthcare have focused on patient flow optimization rather than internal logistics operations that ensure medicine availability. This indicates a clear empirical and conceptual gap in applying DES as a managerial decision-support tool to enhance pharmaceutical warehouse efficiency in Indonesian hospitals. Addressing this gap requires context-specific modeling that leverages existing resources rather than relying on large-scale technological intervention.

This study was conducted collaboratively between the authors from Universitas Pembangunan Nasional "Veteran" Yogyakarta, Indonesia, and Taipei Medical University, Taiwan. This collaboration integrates local empirical knowledge of hospital logistics in Indonesia with international expertise in simulation-based performance analysis and healthcare supply chain management. The study applies a Discrete Event Simulation (DES) approach to analyze and optimize pharmaceutical warehouse operations at Hospital Yogyakarta through three improvement scenarios: (1) reallocating goods and invoice verification tasks to the ordering operator, (2) adding one new operator dedicated to system posting, and (3) combining both strategies.

This research lies in developing a resource-based optimization model that enhances efficiency through workload redistribution and minimal staff expansion—without relying on expensive automation or advanced digital systems. Academically, this study enriches the literature on DES applications in hospital logistics within Indonesia, an area that remains underexplored. Practically, it provides an evidence-based decision-support framework for hospital management to evaluate operational bottlenecks, test alternative strategies, and implement cost-effective improvements. The expected outcome is a measurable reduction in total cycle time by more than 90%, balanced staff utilization, and sustainable enhancement of pharmaceutical logistics performance, demonstrating how international collaboration can strengthen healthcare operations research in developing regions.

METHOD

Research Design

This study adopts a Discrete Event Simulation (DES) approach to evaluate and optimize the operational performance of the pharmaceutical warehouse at Hospital. DES is widely recognized in healthcare operations research for its ability to represent process complexity, variability, and resource interactions in dynamic systems [9], [10], [11].

Study Context

The research focuses on warehouse activities related to inbound logistics (receiving and verification of goods) and outbound logistics (dispensing and distribution to hospital units). These processes were selected because they represent critical points influencing drug availability and overall service quality [12], [13], [14].

Data Collection

Data were collected from two sources:

- Primary data: direct measurement of operational times using a stopwatch, covering supplier arrivals, receiving services, unit requests, and dispensing activities.
- Secondary data: organizational structures, workflow documents, and hospital records related to pharmaceutical warehouse operations.

Data Processing and Input Modeling

Operational time data were analyzed to identify probability distributions for each activity. Distribution fitting was performed using Arena Input Analyzer, ensuring that the stochastic behavior of the system was adequately represented [15], [16].

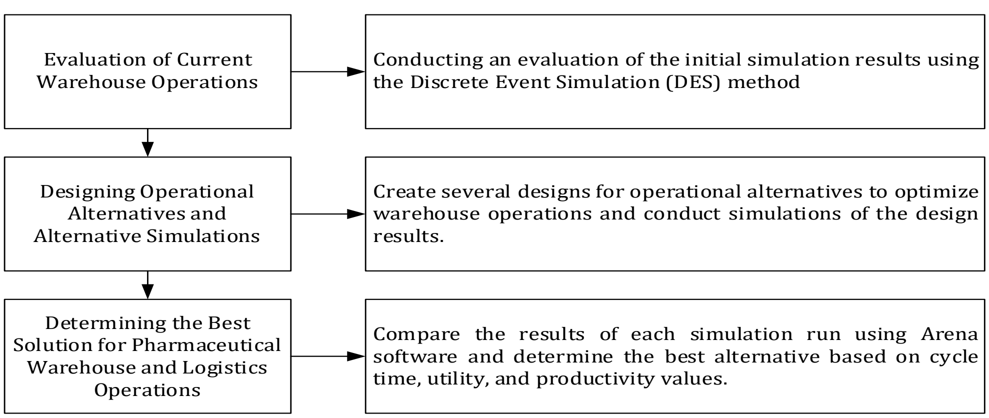


Figure 1. Data Processing and Input Model

Model Development

A conceptual model was constructed using an Activity Cycle Diagram (ACD) to map the interactions among processes and resources [17], [18], [19]. The model was then translated into Arena simulation software. Verification was carried out using model checking procedures to ensure the absence of logical or input errors [20], [21], [22].

Validation

Conceptual validation was conducted through discussions with warehouse supervisors to ensure model realism. Empirical validation was achieved by comparing simulation outcomes with actual operational performance metrics [23], [24], [25].

Scenario Design

Three improvement scenarios were designed and simulated:

1. Task redistribution: assigning goods verification to ordering operators.
2. Additional staffing: introducing one operator dedicated to system posting.
3. Hybrid approach: combining task redistribution with additional staffing.

Performance Metrics

The performance of each scenario was evaluated using three key indicators:

- Cycle time: average time required to complete each process.
- Productivity: ratio of effective output to total input.
- Resource utilization: measure of operator workload distribution efficiency.

The comparison of scenarios against the baseline system enabled the identification of the most effective and feasible strategy for improving warehouse efficiency and service quality [26], [27].

RESULTS

Conceptual Model

The conceptual model illustrates the workflow of receiving and dispensing processes in the hospital pharmaceutical warehouse. This model, presented through an Activity Cycle Diagram (ACD) (Figure 2), describes the interaction between different operational activities. Validation was conducted in consultation with the warehouse supervisor, who confirmed that the conceptual representation accurately reflected the actual system. This validation step ensured that the model could be used as the basis for simulation.

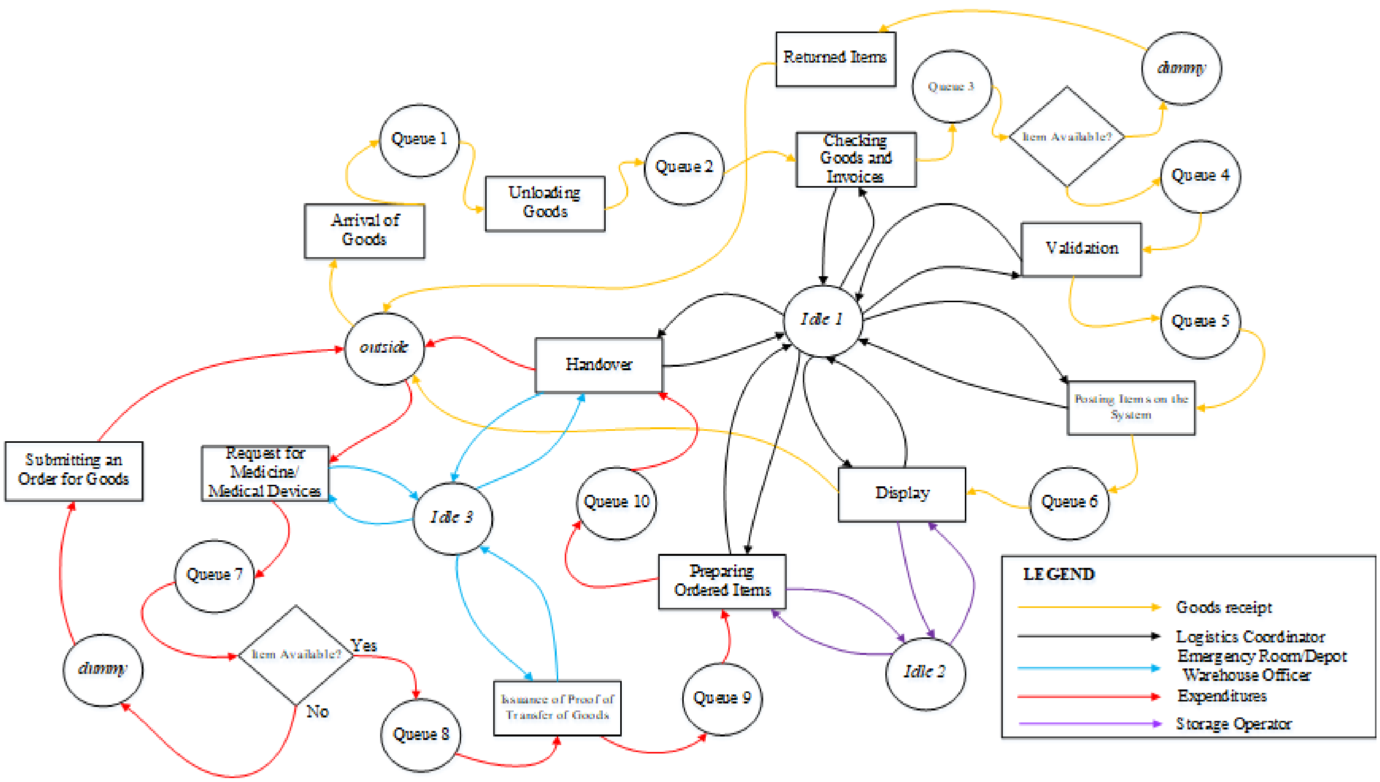


Figure 2. Pharmaceutical Logistics Warehouse Activity Cycle Diagram

Operational activities were analyzed to determine the most suitable probability distributions for simulation input. Table 1 summarizes the fitted distributions for both receiving and dispensing processes. For example, the arrival of goods follows a Beta distribution, while the issuance of transfer documents is best represented by a Normal distribution. The provision of requested items exhibited the highest variability with a Beta distribution and a relatively larger square error value.

Table 1. Distributions for Both Receiving and Dispensing Processes

	Operational Activities	Distribution Types	Expression	Square Error
Reception Department	Arrival of Goods	Beta	-0.5 + 52 * BETA(0.644, 0.976)	0.007835
	Unloading Goods	Beta	2 + 3.62 * BETA(1.05, 1.24)	0.007856
	Checking Goods and Invoices	Beta	2 + 5.89 * BETA(1.59, 1.31)	0.007926
	Validation	Beta	1 + 2.95 * BETA(1.28, 1.38)	0.012353
	Posting Items on the System	Beta	5 + 7 * BETA(1.13, 1.2)	0.005315
	Operational Activities	Distribution Types	Expression	Square Error
Expenditure Section	Request arrival	Beta	-0.5 + 87 * BETA(0.811, 1.35)	0.042369
	Issuance of Proof of Transfer of Goods	Normal	NORM(5.94, 1.77)	0.006650
	Providing Ordered Goods	Beta	4 + 24 * BETA(0.77, 1.01)	0.034469
	Handover	Weibull	2 + WEIB(4, 1.54)	0.014761

Interpretation: These results indicate that activities involving human interaction and manual handling (such as preparing requested items) tend to have longer and more variable cycle times compared to system-driven tasks (such as validation or transfer document issuance). Figure 3 further visualizes the distribution fitting for selected processes, confirming the stochastic nature of the data.

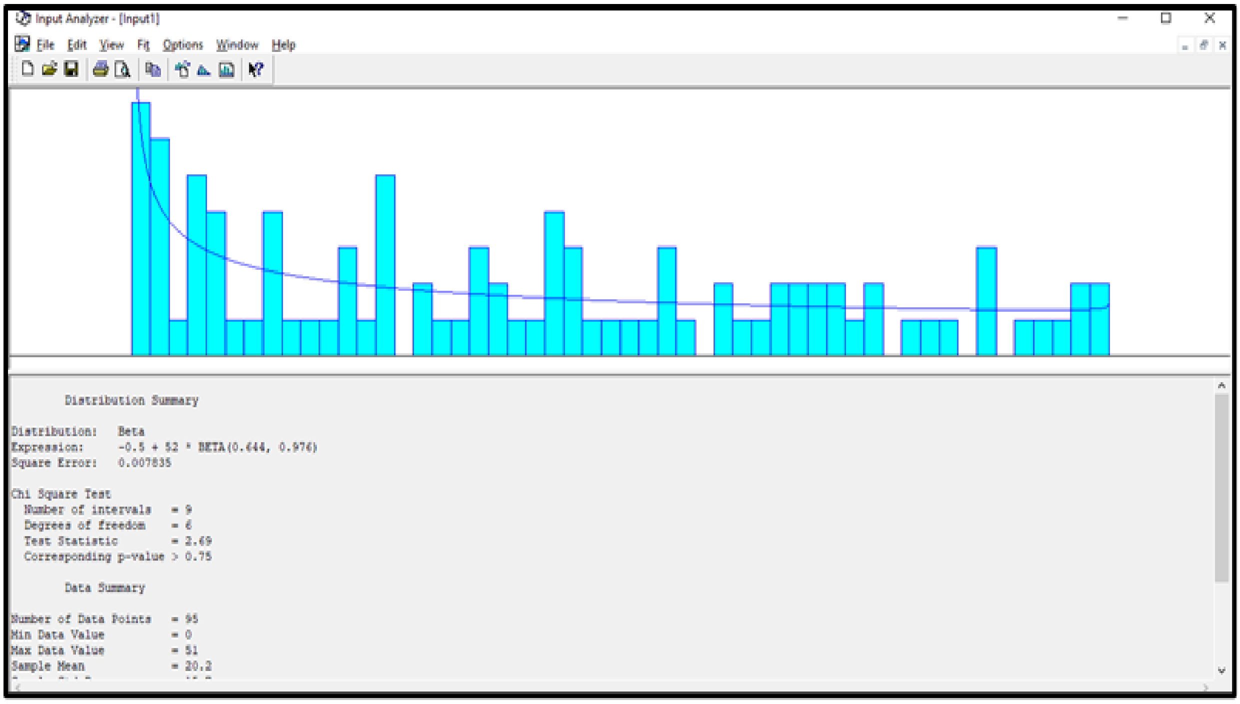
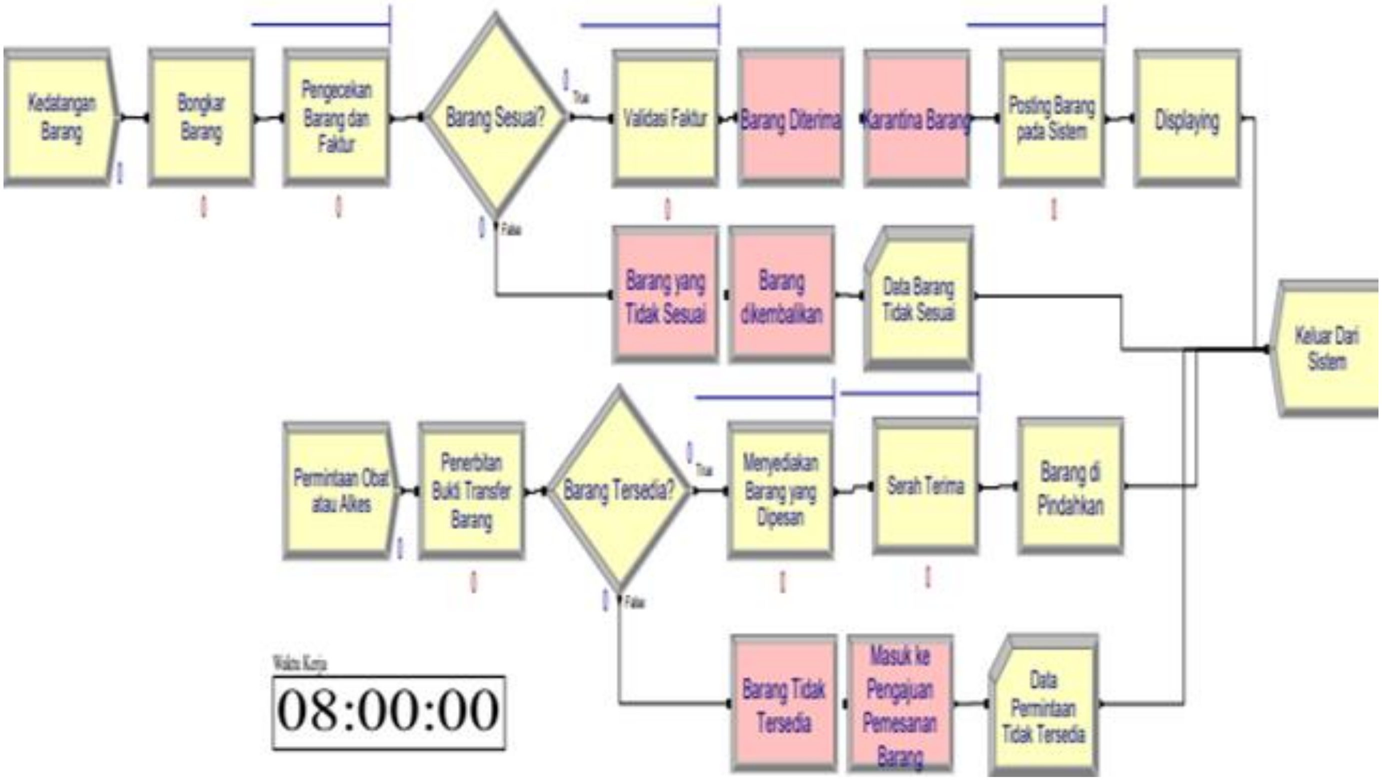


Figure 3. Distribution Summary of Goods Arrival

Operational time data was analyzed to obtain the most appropriate probabilistic distribution. A summary of the fitting results is shown in Table 1. For example, goods arrivals follow a Beta distribution with the equation –0.5 + 52*BETA(0.644;0.976) and a quadratic error of 0.007835, while the validation process also follows a Beta distribution with an average time of 2.95 minutes. In the expenditure section, the issuance of goods transfer certificates follows a Normal distribution (5.94; 1.77), while the handover activity is more consistent with a Weibull distribution. There are nine distributions representing the main activities of a pharmaceutical warehouse, ranging from goods arrival to handover. These fitting results are important inputs in Arena modeling so that simulation behavior approximates actual conditions. Figure 4 shows an example of a distribution summary output for goods arrival activities.

The simulation model was constructed from the verified conceptual framework that had been reviewed and approved by the pharmaceutical logistics warehouse supervisor. This validation ensured that the model accurately reflected the real operational workflow. The final simulation model developed for this study is illustrated in Figure 4.



(Results in Indonesian)
Figure 4. Design Simulation Model

This simulation model illustrates an integrated logistics workflow covering both the receiving and internal distribution of goods in an operational environment such as a hospital or pharmaceutical warehouse. Overall, the process is systematically structured, encompassing key stages such as goods inspection, invoice validation, quarantine, and system posting. The logical branching through decisions like "Goods Suitable?" and "Goods Available?" indicates that the system incorporates both quality control and inventory management mechanisms. However, the simulation remains conceptual since all process durations are recorded as zero, meaning it cannot yet represent real working cycle times. Without time parameters and probability inputs, performance indicators such as throughput time, idle time, and resource efficiency cannot be measured. Moreover, the presence of multiple decision points and process layers may create operational delays if not supported by a responsive information system.

The main potential issues within the model arise in the "Goods Not Suitable" and "Goods Not Available" branches. The process of returning unsuitable goods involves several administrative steps, such as data recording and revalidation, which can create bottlenecks and lengthen the total receiving time. Similarly, the "Goods Not Available" condition requires generating new request data and initiating a new procurement cycle, leading to longer lead times for internal distribution. Additionally, the absence of a direct feedback mechanism from "Goods Not Suitable" to the supplier results in a lack of a closed-loop quality improvement process. In summary, while the model is structurally coherent and logically sound, it requires the inclusion of actual time parameters, error probabilities, and real-time data integration to accurately represent operational dynamics and identify critical inefficiency points in the logistics process.

Table 2. Among the activities, "providing the requested items" had the highest cycle time of 837.73 minutes per week, indicating it as the main bottleneck.

Table 2. Provides A Quantitative Overview of The Logistics Simulation Results

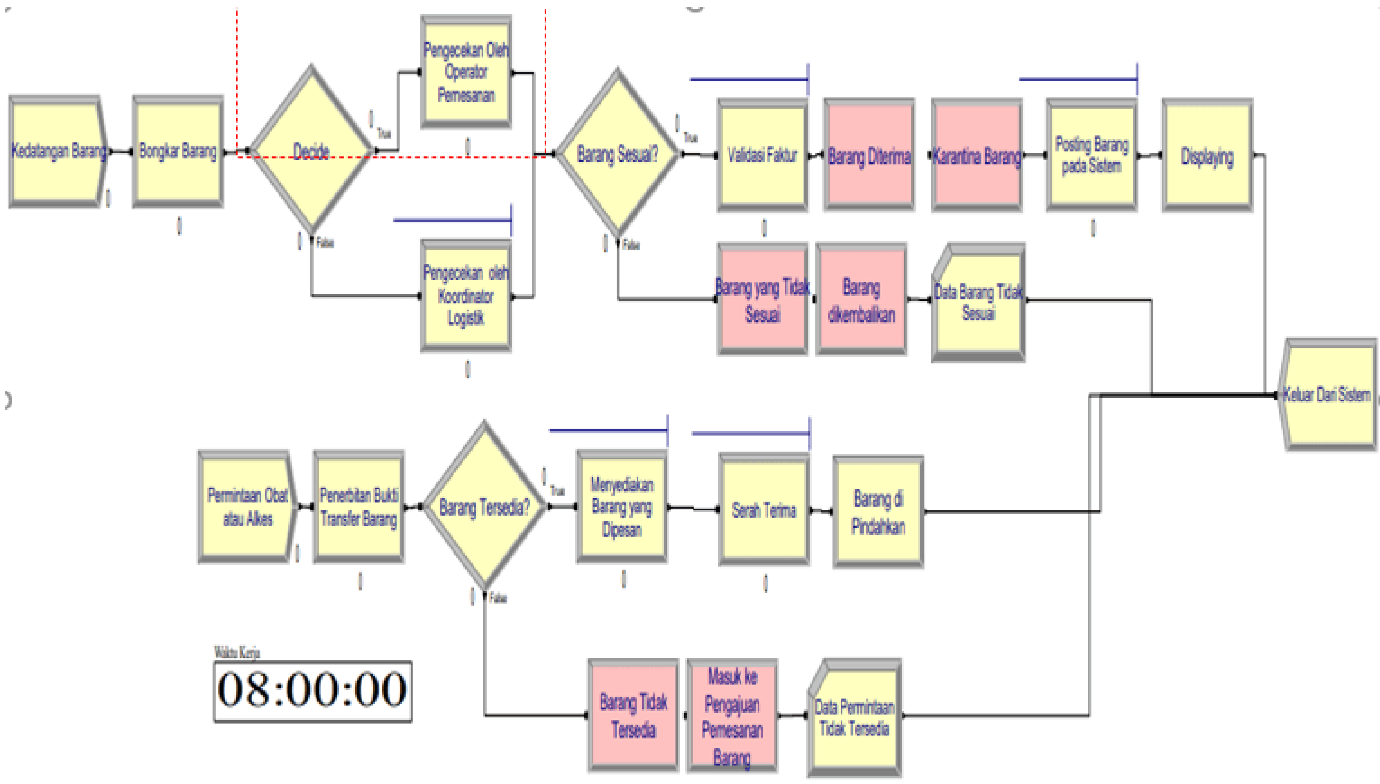
Entity	Process	Cycle Time (Minutes/Week)	Number In	Number Out
Arrival Goods	Unloading Goods	421.34	117	71
	Checking Goods and Invoices	511.84		
	Validation	196.32		
	Posting Items on the System	563.03		
Request Goods	Issuance of Proof of Transfer of Goods	451.27	76	56
	Providing Ordered Goods	837.73		
	Handover	268.91		
	Total	**3250.44**	**193**	**127**

The data in Table 2 provides a quantitative overview of the logistics simulation results, showing that the total weekly cycle time reaches 3,250.44 minutes, reflecting a relatively long process duration across all stages. The longest activity occurs in preparing ordered goods (837.73 minutes/week), followed by posting goods into the system (563.03 minutes/week) and checking goods and invoices (511.84 minutes/week). These results indicate that the most time-consuming processes are related to administrative and system-recording activities, which align with the earlier simulation flow that emphasized validation and posting as critical control points. Meanwhile, the number of entities processed (Number In = 193; Number Out = 127) shows a significant throughput imbalance, suggesting that not all incoming goods are successfully processed and distributed within the same week. This discrepancy highlights potential process delays, queue accumulation, or inefficiencies in the validation and system-entry phases.

The breakdown between goods arrival and request fulfillment processes also reveals key operational issues. At the goods receiving stage, there is a notable gap between goods checked (117) and goods successfully posted in the system (71), implying that about 40% of goods may still be pending due to validation or data-entry bottlenecks. Similarly, at the demand fulfillment stage, the high cycle time for preparing goods (837.73 minutes) compared to the smaller transaction volume (76 in, 56 out) indicates inefficiency in inventory retrieval or internal coordination. These findings reinforce that administrative and manual handling processes dominate operational time, reducing system responsiveness. To improve efficiency, automation in posting activities, optimized manpower allocation in the preparation stage, and real-time synchronization between receiving and dispatch units are recommended. Such adjustments would shorten cycle times, balance input–output flow, and enhance overall logistics performance consistency.

Design and Running Simulation Proposal

Figure 5 illustrates the proposed Alternative Model 1, which restructures the goods receiving process by assigning the Ordering Operator additional responsibility for inspecting incoming goods and verifying invoices. This modification aims to streamline administrative validation, reduce process redundancy, and enhance synchronization between procurement and logistics functions. The model serves as an initial improvement to address bottlenecks in the early verification phase observed in the baseline process simulation.



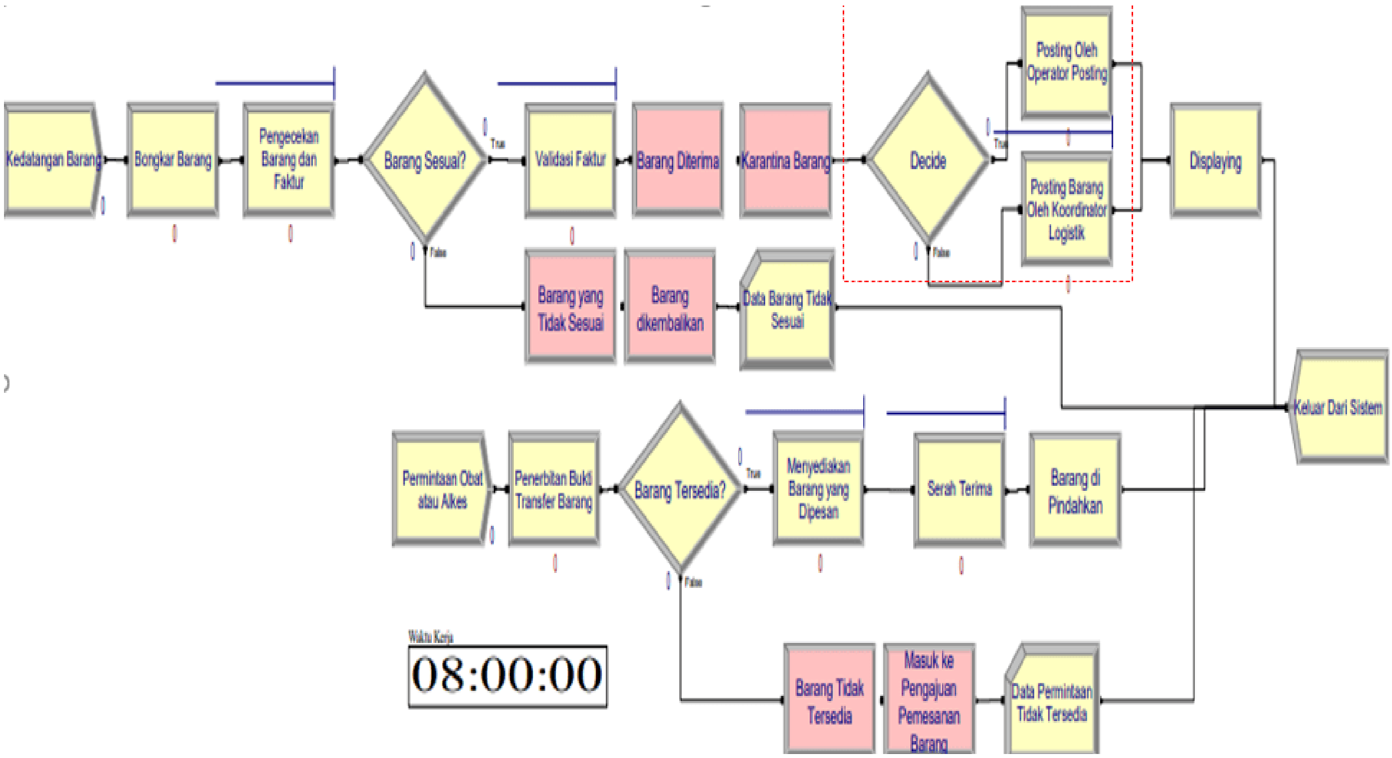
(Results in Indonesian)

Figure 5. Alternative Simulation Model I

The Alternative Model 1 introduces a modification to the goods receiving process by assigning the Ordering Operator an additional task — performing both goods and invoice inspections upon arrival. This adjustment aims to streamline administrative validation at the early stage of the receiving process, reduce coordination delays, and ensure that the verification of order accuracy is carried out directly by the same personnel responsible for order documentation. By integrating the roles of order administration and initial inspection, the model enhances process continuity between procurement and warehouse functions, minimizing communication gaps that often occur when verification tasks are split among different departments.

In terms of advantages, this approach increases efficiency in early validation, as the ordering operator has direct access to purchase data and can immediately confirm whether the received goods match the purchase order and accompanying invoice. It also minimizes administrative handovers and potential document mismatches, leading to faster decision-making at the "Goods Suitable?" stage. However, the main drawback lies in the potential workload increase for the ordering operator, who now handles both administrative and physical inspection tasks. Without proper time allocation or support systems, this role expansion may result in processing delays during peak delivery periods. Additionally, if the operator lacks technical knowledge of product specifications, inspection accuracy may decrease, potentially allowing nonconforming goods to pass initial validation. Therefore, while Alternative 1 strengthens administrative control and shortens process time, it requires proper training, clear work delegation, and supporting digital tools to maintain accuracy and avoid overburdening the operator.

Figure 6 presents Alternative Model 2, which enhances the efficiency of the goods posting process by introducing an additional operator dedicated to system data entry. This structural adjustment separates administrative tasks from logistical activities, allowing both to occur simultaneously and reducing overall process cycle time. The model aims to improve data accuracy, accountability, and synchronization between physical goods handling and digital inventory updates within the logistics workflow.



(Results in Indonesian)

Figure 6. Alternative Simulation Model II

The Alternative Model 2 focuses on improving the efficiency of the posting process by adding a new operator specifically responsible for posting goods into the system. This adjustment addresses one of the key bottlenecks identified in the initial model — the accumulation of administrative tasks at the data entry stage. In the original workflow, the logistics coordinator handled both physical verification and system posting, which often led to delays due to task overlap. By introducing a dedicated *Posting Operator*, the model separates administrative posting from physical logistics work, allowing both processes to occur simultaneously and reducing the overall cycle time between validation, quarantine, and displaying.

From a performance perspective, this structural change offers several advantages. First, it enhances process specialization, as the new operator focuses solely on data accuracy and timely input into the inventory system. This specialization not only improves data consistency but also reduces the likelihood of posting errors caused by multitasking. Second, by running posting and logistics activities in parallel, the model increases the system's overall throughput and responsiveness, allowing inventory updates to occur more quickly after goods are validated. Additionally, this configuration strengthens accountability because each employee's responsibility is clearly defined — the logistics coordinator focuses on physical movement, while the posting operator ensures digital synchronization.

However, the potential drawbacks of this model include increased operational costs due to the addition of a new employee, as well as the need for coordination between the posting operator and the logistics coordinator to prevent data duplication or posting delays. If communication between these two roles is not well managed, mismatches between physical and digital inventory data may still occur. Furthermore, without a well-integrated system, simultaneous operations could create synchronization errors or double postings. In conclusion, while Alternative 2 significantly improves process speed and accuracy through task specialization, its success depends on strong coordination mechanisms and real-time information sharing between logistics and administrative functions to ensure that physical and digital inventory flows remain aligned.

Figure 7 illustrates Alternative Model 3, which integrates the improvements from both previous alternatives by combining task reassignment and additional workforce. In this model, the Ordering Operator is assigned to inspect goods and verify invoices, while a new Posting Operator is added to handle system data entry. This hybrid structure aims to optimize process flow, reduce administrative bottlenecks, and enhance both accuracy and efficiency in the goods receiving and posting stages of the logistics operation.

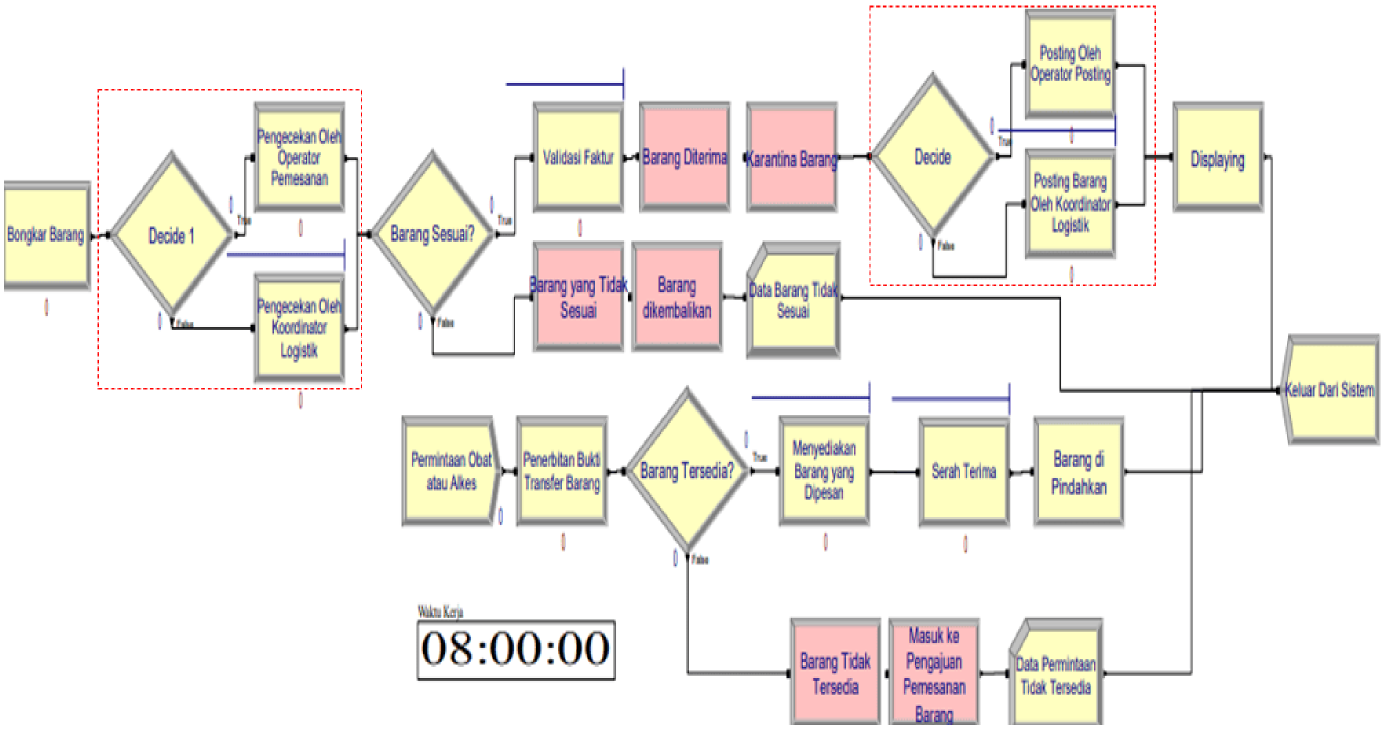


Figure 8. Alternative Simulation Model III

The Alternative Model III represents a comprehensive improvement that combines the strengths of Alternative Models I and II. In this configuration, the workflow introduces two critical enhancements: (1) assigning the *Ordering Operator* the additional responsibility of checking the goods and invoices upon arrival, and (2) adding a new employee specifically dedicated to *posting goods into the system*. This dual modification aims to reduce process delays caused by task overload in earlier models and to ensure that both verification and data-entry activities are carried out efficiently and accurately. The model thus enhances coordination between administrative and logistical functions while maintaining the standard 8-hour operational cycle per shift.

From an analytical perspective, Alternative III demonstrates significant advantages in terms of clarity, workload distribution, and system reliability. By delegating the verification of goods and invoices to the Ordering Operator, the process ensures that administrative validation occurs immediately after unloading, minimizing idle time and reducing errors before the physical validation stage. Meanwhile, assigning a dedicated posting employee improves data accuracy and shortens the overall posting duration since the task no longer depends on multitasking personnel. This structure also enables parallel processing between administrative verification, quarantine, and system posting, thereby enhancing throughput and reducing bottlenecks.

However, the model also presents certain potential drawbacks. The addition of a new employee increases operational costs, and the inclusion of multiple verification layers may initially require adjustments in coordination and communication flow. Without proper digital synchronization between the Operator Posting and the Logistics Coordinator, redundant data entries or system inconsistencies may still occur. Furthermore, the reliance on manual decision nodes ("Decide 1" and "Decide") means that efficiency still depends on timely human decision-making rather than full automation. Overall, Alternative III can be considered the most balanced and effective structure among the three models—offering higher accuracy, accountability, and workflow efficiency—provided that supporting digital systems and coordination protocols are properly implemented.

Alternative Simulation Results

Table 3 presents the comparison of simulation performance results between the existing real system and the proposed alternative models. The evaluation focuses on measuring cycle time efficiency and process throughput (Number In and Number Out) across each activity involved in goods receiving and distribution. This analysis aims to identify which alternative scenario provides the greatest improvement in operational performance and system productivity.

Table 3. Comparison of Simulation Performance Results

	Activity	Cycle Time				Number In				Number Out			
		Real System	I	II	III	Real System	I	II	III	Real System	I	II	III
Reception	Unloading Goods	3.64	3.62	3.49	3.65	117	119	109	114	71	107	108	113
	Checking Goods and Invoices	160.90	5.73	17.13	5.24								
	Validation	167.11	123.4	14.10	10.32								
	Posting Items on the System	162.57	119.8	8.56	8.23								
Expenditure	Issuance of Proof of Transfer of Goods	5.92	5.73	6.37	5.43	76	67	66	61	56	60	65	60
	Providing Ordered Goods	149.23	108.4	20.1	19.40								
	Handover	147.03	105.1	17.04	13.30								

The simulation results presented in the table demonstrate that the implementation of the three improvement alternatives had a significant impact on operational efficiency, particularly in the goods receiving and distribution processes. In the current system, the activities with the longest cycle times were goods and invoice inspection (160.90 minutes) and validation (167.11 minutes), which served as the primary bottlenecks causing overall process delays. After implementing the proposed improvements, cycle times decreased drastically across all alternatives, with Alternative III showing the best performance—only 5.24 minutes for inspection and 10.32 minutes for validation. This substantial reduction indicates that redistributing responsibilities between the ordering operator and logistics coordinator, along with the addition of a new operator dedicated to system posting, effectively eliminated task overlap and accelerated administrative verification. Furthermore, the posting activity also improved remarkably, reducing from 162.57 minutes to 8.23 minutes, highlighting the efficiency gained through task specialization and improved digital synchronization compared to the original centralized workflow.

From a productivity standpoint, the Number In and Number Out values exhibit better balance, reflecting an increase in process capacity and smoother material flow. In the real system, there was a notable gap between goods received (117 units) and goods processed or dispatched (71 units), indicating accumulation delays in administrative and data entry processes. However, under Alternative III, the number of processed goods rose to 113 units, nearly matching the total input (114 units), demonstrating a more stable and efficient throughput. These findings confirm that the combination of task redistribution and the addition of a dedicated operator not only shortened processing time but also improved synchronization between physical and digital workflows. Therefore, it can be concluded that Alternative III represents the most optimal scenario, achieving over a 90% reduction in cycle time compared to the current system while significantly enhancing process balance and throughput key indicators of improved efficiency in modern logistics management systems.

DISCUSSION

The results of this study reveal that the activity of providing the ordered goods constitutes the most significant bottleneck in the hospital pharmaceutical warehouse, with an average cycle time of 837.73 minutes per week. In contrast, other tasks such as validation require relatively little time and therefore do not contribute substantially to delays. This bottleneck is exacerbated during peak hours (09:00–10:55) and by the assignment of dual tasks when suppliers (PBF) arrive, namely simultaneous receiving and checking. Such conditions lead to backlog, delayed distribution, and ultimately stockouts in patient care units. These findings are consistent with [28], [29], who demonstrated that unbalanced staff allocation is a major cause of bottlenecks in healthcare service flows.

Simulation experiments with three alternative scenarios indicate that Alternative III a combination of redistributing the checking task to the ordering operator and adding one operator for system posting—emerged as the most effective solution. This scenario reduced cycle time, improved productivity from 68% to 99%, and decreased excessive staff utilization. These outcomes align with [30], who emphasized the importance of process redesign and human resource optimization prior to heavy investment in automation technologies [31].

From a methodological standpoint, the use of Discrete Event Simulation (DES) proved effective in identifying bottlenecks and testing improvement scenarios. This supports the systematic review published in Applied Sciences (2023), which highlighted DES as the most widely used method in healthcare operations due to its ability to capture process complexity and stochastic demand. Model validation with warehouse supervisors, as conducted in this study, further reflects best practices recommended by [32], stressing stakeholder engagement in the validation stage to ensure managerial acceptance.

With regard to inventory management, the integration of DES with inventory optimization parameters (s, S), as demonstrated by [33], could be a promising extension of this research. Their study showed that combining clustering with simulation optimization significantly reduced inventory costs while maintaining service levels. Similarly, [34] in the Indonesian context revealed that simulation-based drug inventory models during the COVID 19 pandemic effectively mitigated stockouts despite highly fluctuating demand. Thus, coupling the operational warehouse simulation in this study with inventory optimization could provide more comprehensive and sustainable recommendations.

Comparisons with other studies underscore the robustness of these findings. [35], [36], [37] observed that task redistribution is often more effective than merely adding staff. [38] found that additional staffing is only effective when targeted precisely at bottleneck stations, not dispersed arbitrarily. These findings support the argument that hybrid strategies, such as Alternative III, are superior to redistribution alone (Alternative I) or isolated staffing increases (Alternative II).

Other empirical evidence also highlights the value of process redesign [39], studying outpatient pharmacies, reported that better task sequencing reduced patient waiting times by up to 35%. [36], [37], [38] further stressed the importance of sensitivity testing to ensure the robustness of solutions under demand surges. Accordingly, the interventions proposed in this study should also be tested under scenarios of extreme demand variability to confirm their resilience.

Attention should also be paid to the risk of bottleneck shifting. [34], [35], [40] cautioned that alleviating workload in one activity may inadvertently create new bottlenecks elsewhere if left unmonitored. In this case, transferring the checking task to the ordering operator could potentially increase workload at the early stage of the process. This underlines the importance of continuous monitoring after implementation, as similarly recommended by [30] in their Lean–DES evaluation of hospital operations.

Cost implications are another critical consideration. [20] demonstrated that low-cost process-based interventions often yield faster return on investment compared to large-scale technology adoption. This resonates with the present findings, where Alternative III offers significant performance gains at relatively low cost. Nevertheless, the additional salary expense for one new operator must be carefully weighed against the time savings and reduced service failures.

Several limitations of this study should be acknowledged. First, the dataset was based on direct observation over a specific period and may not fully capture seasonal demand variability. Second, the model does not yet account for the learning curve effect that arises when staff take on new responsibilities. [19] found that task transitions typically involve a temporary decline in performance before staff adapt to their new roles. Future research should therefore integrate learning curve dynamics and supplier arrival variability into the simulation model.

Despite these limitations, this research contributes meaningfully to the practice of hospital pharmaceutical logistics management. By employing DES, management can quantitatively test alternative policies before field implementation, thereby minimizing the risks of trial-and-error approaches. Such evidence-based decision making is increasingly recognized as essential for modern healthcare systems [26][13].

CONCLUSION

This study confirms that applying Discrete Event Simulation (DES) is an effective approach to analyze and improve the operational efficiency of hospital pharmaceutical warehouses. The simulation results reveal that the main problems in the current system occur during goods checking, validation, and posting activities, which create workload accumulation and distribution delays. Among the three proposed improvement scenarios, Alternative III a combination of reassigning verification tasks to the ordering operator and adding a new operator for system posting proved to be the most optimal solution. This alternative successfully reduced the total process cycle time by more than 90%, increased productivity by up to 99%, and balanced operator workloads without adding system complexity. The findings indicate that performance improvement in pharmaceutical logistics can be achieved through work redistribution and human resource optimization rather than through expensive automation technologies.

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