

Integrated MRP, Standard Work, and FEFO Model to Reduce Stockouts of Medical-Surgical Supplies

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Abstract

This study proposes and validates an integrated model to reduce stockouts of medical surgical supplies in a Peruvian trading company, addressing a critical challenge in healthcare supply chain management where inventory failures directly affect service continuity and operational efficiency. A root cause analysis identified four key operational issues: reactive purchasing based on past sales, manual recording errors, lack of prioritization of near expiry products, and absence of expiration date verification during reception, which collectively lead to inventory inaccuracies and supply disruptions. To address these gaps, the proposed model integrates four complementary tools, Machine Learning for demand forecasting, Material Requirements Planning (MRP) for replenishment scheduling, Standard Work (SW) for process standardization, and First Expired, First Out (FEFO) for efficient inventory rotation, structured as a sequential and interdependent system that enables data driven decision making and improved operational control. Validation was carried out through a hybrid approach combining a field pilot for the Machine Learning and Standard Work components with a discrete event simulation in Arena for the MRP and FEFO components, allowing evaluation under both real and controlled conditions. The results demonstrate a 40.6% reduction in the Stockout Index (from 0.0577 to 0.0343), a 28% decrease in the Inventory Discrepancy Index (from 25% to 18%), a forecasting accuracy of 79%, and a 54.6% reduction in obsolescence (from 0.0793 to 0.036), evidencing a significant improvement in inventory performance.

Keywords

Medical supply chain, inventory management, stockout, demand forecasting, FEFO.

1. Introduction

The continuous availability of medical-surgical supplies is essential to ensure the operational continuity of healthcare services, particularly in surgical environments where the absence of materials may compromise patient care. In the Peruvian context, commercial companies face structural limitations such as high dependence on imports, demand variability, and limited adoption of technological systems, which significantly increases the risk of stockouts (Caballero and Urcia 2021; OECD 2022).

Dependence on international suppliers exposes the supply chain to logistical disruptions, delays in delivery times, and regulatory restrictions, making supply planning more difficult (Van Dijk 2020; Ivanov 2021). This issue is further aggravated by the use of traditional replenishment approaches based on recent historical consumption, which fail to capture demand variability and seasonality, leading to reactive decision-making that increases the likelihood of stockouts (Govindan et al. 2020; Khanna et al. 2020).

In this context, stockouts represent a critical problem due to their impact on the continuity of clinical procedures, the increase in operational costs, and the loss of reliability perceived by customers (Singh and Gupta 2020; Rossetti and Smith 2021). Additionally, the lack of standardization in logistical processes, manual recording errors, and the absence of expiration-based rotation criteria contribute to inventory discrepancies and losses due to obsolescence (Jain and Rathore 2019; Chang et al. 2022).

Previous studies have shown that stockouts in healthcare supply chains are rarely caused by a single factor. Instead, they result from the interaction of deficiencies in demand forecasting, replenishment planning, inventory control, operational execution, and inventory rotation practices (Govindan et al. 2020; Khanna et al. 2020; Jain and Rathore 2019; Chang et al. 2022). Consequently, organizations often implement isolated improvement initiatives that address only one dimension of the problem, limiting their ability to achieve sustainable improvements in inventory performance.

Although the literature has addressed tools such as Machine Learning, Material Requirements Planning (MRP), Standard Work (SW), and First Expired First Out (FEFO) individually, there is a gap in their integration into a single and sequential model, particularly in companies with low levels of digitalization (Fahimnia and Jabbarzadeh 2021; Souza and Jaber 2024). While previous studies have demonstrated the effectiveness of these approaches in specific inventory management activities, limited research has proposed a unified framework capable of simultaneously addressing demand forecasting, replenishment planning, process standardization, inventory accuracy, and product obsolescence within medical-surgical supply distribution companies.

To address this gap, this research proposes an integrated inventory management model that combines Machine Learning-based demand forecasting within the MRP planning process, together with Standard Work and FEFO as complementary operational control mechanisms. The proposed framework links forecasting, planning, execution, and inventory rotation through a sequential decision-support structure designed to address the root causes of stockouts from a systemic perspective. Furthermore, the study contributes to the literature by validating the proposed model through a hybrid approach that combines field implementation and discrete-event simulation, providing both practical and analytical evidence of its effectiveness in improving inventory performance.

1.1 Objectives

The main objective of this research is to design an inventory management model based on demand forecasting, process standardization, and product rotation to reduce the stockout index in a medical-surgical supply trading company.

Specific objectives include:

- Identify the main operational causes of stockouts through root cause analysis.
- Develop a demand forecasting model using Machine Learning techniques, evaluated through forecast accuracy metrics.
- Design a replenishment planning system based on Material Requirements Planning (MRP) to improve inventory availability, measured through the reduction of the Stockout Index (ISI).
- Standardize inventory management processes through the implementation of Standard Work (SW), aiming to reduce discrepancies between physical and recorded inventory, measured using the Inventory Discrepancy Index (IDI).
- Implement a First Expired, First Out (FEFO) policy to improve inventory rotation and reduce product obsolescence, measured through the Obsolescence Rate.
- Validate the effectiveness of the proposed model through a comparative analysis of key performance indicators (ISI, IDI, forecast accuracy, and obsolescence rate) between the current and improved scenarios.

2. Literature Review

The continuous availability of medical-surgical supplies is essential to ensure the operational continuity of healthcare services, particularly in surgical environments where the absence of materials may compromise patient care. In the Peruvian context, commercial companies face structural limitations such as high dependence on imports, demand variability, and limited adoption of technological systems, which significantly increases the risk of stockouts (Caballero and Urcia 2021; OECD 2022).

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3. Methods

This research adopts a mixed methodological approach that integrates a diagnostic analysis, the design of an integrated inventory management model applied to a Peruvian medical-surgical supply trading company and the validation of the proposed model.

The literature review was conducted using the Scopus, ScienceDirect, and ProQuest databases, focusing on peer-reviewed articles published between 2019 and 2024. Keywords such as *medical supply chain*, *inventory management*, and *stockout* were combined using Boolean operators. The screening process considered publication period, thematic relevance, accessibility, and journal quality. After the selection process, 45 applied studies were retained and synthesized into three categories: causes of stockouts, operational consequences, and mitigation strategies. The reviewed literature indicates that stockouts are primarily driven by deficiencies in demand planning, lack of digital integration, and ineffective inventory control systems (Govindan et al., 2020; Hiatt et al., 2024; Munyaka & Yadavalli, 2022). Furthermore, prior studies emphasize the importance of integrating Machine Learning techniques and Material Requirements Planning (MRP) systems to improve forecasting accuracy and replenishment decisions (Muchenje et al., 2024; Pasupuleti et al., 2024; Muyulema-Allaica et al., 2024).

Following the literature review, a diagnostic analysis was conducted using historical operational data from the case study company to assess the current inventory management system. Through root cause analysis, four critical factors were identified: reactive purchasing based on previous sales, manual errors in inventory records, lack of prioritization of near-expiry products, and absence of expiration-date verification during product reception. These findings are consistent with the challenges identified in the literature and constitute the basis for the proposed solution.

The identified root causes are summarized in Figure 1. As shown, the problem is structured through a cause-and-effect relationship that links operational deficiencies to key consequences such as demand misalignment, inventory discrepancies, and product obsolescence. These issues ultimately result in stockouts and inefficiencies within the supply chain. Additionally, the figure highlights the interdependence between causes, indicating that stockouts arise from the interaction of multiple operational and managerial factors rather than from a single isolated issue.

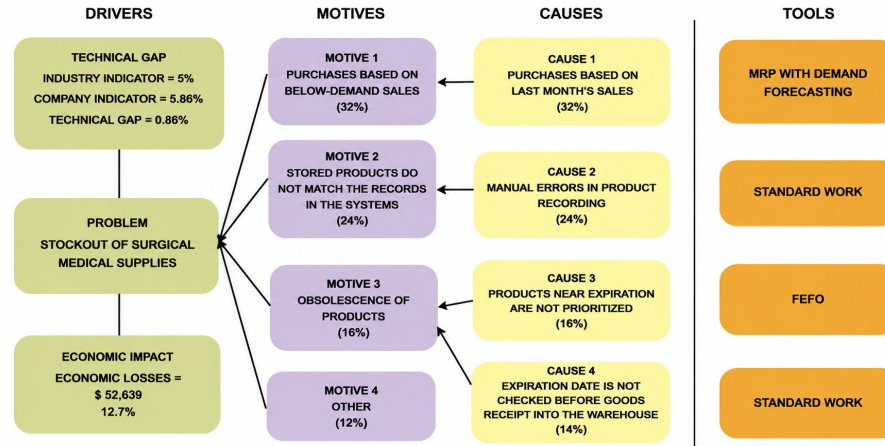


Figure 1. Root causes analysis

Based on this diagnosis, an integrated solution model was developed, structured as a sequential and interdependent system composed of Machine Learning-based demand forecasting, Material Requirements Planning (MRP), Standard Work (SW), and First Expired, First Out (FEFO). The sequence of the model reflects the operational logic of inventory management. Machine Learning addresses demand uncertainty by generating demand forecasts, which constitute the primary input for the MRP planning process. MRP then translates these forecasts into replenishment decisions. Subsequently, Standard Work supports the execution and control of inventory processes by reducing operational variability and inventory recording errors, while FEFO improves inventory rotation and minimizes obsolescence. Consequently, the output generated by each component becomes the input for the subsequent stage, creating an integrated inventory management system rather than a set of isolated improvement initiatives.

Within this structure, the Machine Learning component employs a Random Forest regression model to forecast demand using historical data. As shown in Figure 2, this stage represents the initial input of the system, generating demand forecasts that feed the planning process. The performance of the forecasting model is evaluated using forecast accuracy, which compares predicted demand with actual observed demand.

The MRP component translates these forecasts into replenishment decisions by determining order quantities and timing based on projected demand, available inventory, and supplier lead times. The net requirement for each item is calculated as:

$$\text{Net Requirement} = \text{Forecast} - \text{Available Inventory} + \text{Safety Stock}$$

To account for demand variability and supply uncertainty, safety stock (SS) is incorporated and calculated as:

$$SS = Z * \sigma_d * \text{sqrt}(LT)$$

where Z represents the service level factor, σ the standard deviation of demand, and LT the lead time.

At the operational level, Standard Work procedures are implemented to ensure process standardization and improve data accuracy, particularly in inventory recording and product handling. In parallel, the FEFO policy optimizes

inventory rotation by prioritizing products with earlier expiration dates, which is critical in healthcare supply chains (Herron et al., 2022). These components collectively ensure alignment between planning and execution processes.

The overall structure follows a sequential logic in which each component addresses a specific operational cause and feeds the next stage, forming an integrated and data-driven system that enhances decision-making and operational control, as illustrated in Figure 2.

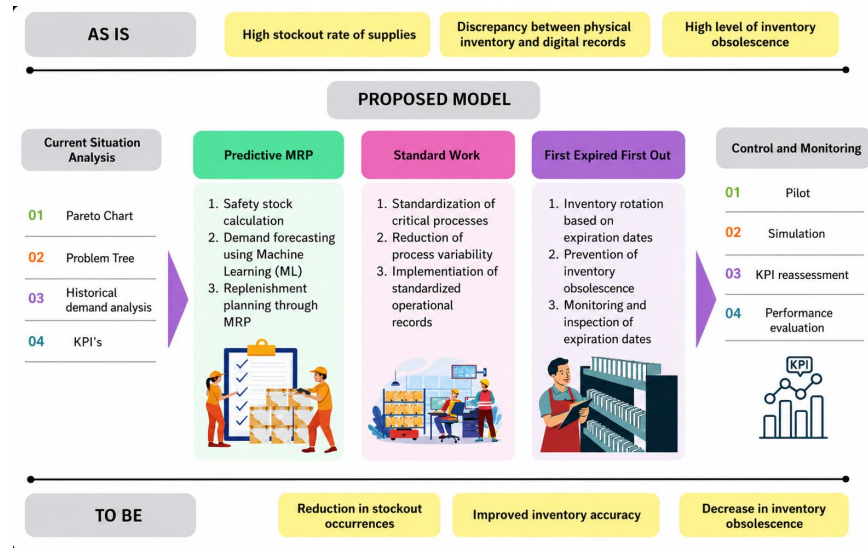


Figure 2. Conceptual model of the proposed integrated system

During the data analysis stage, key performance indicators (KPIs) were defined to evaluate the performance of the inventory management system. As represented in the control and monitoring stage of Figure 2, these indicators include the Stockout Index (ISI), which measures the proportion of unmet orders; the Inventory Discrepancy Index (IDI), which evaluates the difference between physical and recorded inventory; forecast accuracy; and inventory obsolescence.

4. Data Collection

The data used in this research was obtained from a Peruvian company dedicated to the import and commercialization of medical and surgical supplies. The company manages its inventory through Excel-based records, where product entries and exits are manually registered by code and batch.

The dataset consists of historical operational data collected over a 12-month period, including information related to inventory, sales, and procurement processes.

The data was structured into the following categories:

1. Inventory data: stock levels, product codes, batch identification, expiration dates, and inventory movements.
2. Sales data: historical demand per product and sales behavior over time.
3. Procurement data: supplier lead times and replenishment conditions.
4. Operational data: records of discrepancies, expired products, and errors associated with manual inventory registration.

This information was used to evaluate key performance indicators of the current system, particularly the Stockout Index (ISI), which reflects the frequency of inventory shortages in relation to demand. Prior to analysis, a data preprocessing stage was carried out, including validation of records, correction of inconsistencies, and organization of data to ensure reliability for modeling and simulation purposes. Additionally, qualitative information was obtained through direct observation of warehouse operations, allowing the identification of operational deficiencies such as

lack of standardized procedures and insufficient control of expiration dates. These findings complemented the quantitative analysis and supported the design of the proposed solution model.

5. Results and Discussion

The results obtained from the implementation of the integrated model (Machine Learning, MRP, Standard Work, and FEFO) demonstrate a significant improvement in inventory management performance. The analysis compares the initial scenario (As-Is) with the improved scenario (To-Be), considering key performance indicators such as the Stockout Index (ISI), Inventory Discrepancy Index (IDI), forecasting accuracy, and obsolescence rate.

Overall, the results indicate that the proposed model not only reduces stockouts but also improves operational stability, data reliability, and inventory efficiency, generating both operational and economic benefits.

5.1 Numerical Results

The numerical results are presented below. First, the Inventory Stockout Index (ISI) is shown, which reflects a significant improvement after the implementation of the proposed model. This indicator aims to measure the frequency at which inventory is not available to meet demand. The formula used to determine the Inventory Stockout Index (ISI) is presented below.

$$ISI = \frac{\text{Unmet Orders due to stockout}}{\text{Total Orders}} \times 100$$

The ISI decreased from 5.7% in the current situation to 3.4% in the proposed model scenario, indicating a reduction in stockout occurrences and an improvement in product availability. This is shown in Table 1.

Table 1. Inventory Stockout Index

Inventory Stockout Index (ISI)		
Current situation	Proposed model situation	Units
5.7	3.4	Percentage

Second, the Inventory Discrepancy Index (IDI) is presented, which reflects an improvement in inventory accuracy after the implementation of the proposed model. This indicator aims to measure the difference between physical inventory and recorded inventory. The formula used to determine the Inventory Discrepancy Index (IDI) is presented below.

$$IDI = \frac{\text{Physical Inventory} - \text{Recorded Inventory}}{\text{Recorded Inventory}}$$

The IDI decreased from 25% in the current situation to 18% in the proposed model scenario, indicating a reduction in discrepancies and greater reliability of inventory records as shown in Table 2.

Table 2. Inventory Discrepancy Index (IDI)

Inventory Discrepancy Index (IDI)		
Current situation	Proposed model situation	Units
25	18	Percentage

Third, the Forecast Accuracy is presented, which reflects the performance of the forecasting module integrated into the proposed model. This indicator aims to measure how accurately the model predicts demand behavior. The formula used to determine the Forecast Accuracy is presented below.

$$FA = \left(1 - \frac{|\text{Demanda real} - \text{demanda pronosticada}|}{\text{Demanda real}}\right) \times 100$$

The proposed model achieved a forecasting accuracy of 79%, demonstrating its ability to provide reliable demand estimations and support planning decisions as shown in Table 3.

Table 3. Forecast Accuracy

Forecast Accuracy		
Current situation	Proposed model situation	Units
N/A	79	Percentage

Finally, the Obsolescence Rate is presented, which reflects an improvement in inventory rotation after the implementation of the proposed model. This indicator aims to measure the proportion of products that become obsolete due to expiration. The formula used to determine the Obsolescence Rate is presented below.

$$\text{Obsolescence rate (\%)} = \frac{\text{Valor de insumos vencidos}}{\text{Valor total de inventario}} \times 100$$

The obsolescence rate decreased from 7% in the current situation to 4.9% in the proposed model scenario, indicating better management of products close to their expiration date as shown in Table 4.

Table 4. Obsolescence Rate

Obsolescence Rate		
Current situation	Proposed model situation	Units
7.2	3.6	Percentage

5.2 Graphical Results

The following compares the current and final performance levels of the main inventory indicators and highlights the magnitude of the changes achieved after implementation (Figure 3).

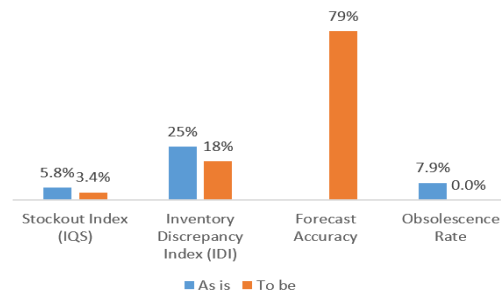


Figure 3. Performance improvement across key inventory indicators

The Inventory Stockout Index (ISI) decreased from 5.7% to 3.4%, representing a 40.6% reduction. This result is consistent with previous studies reporting improvements in inventory performance through integrated forecasting and replenishment systems (Fahimnia and Jabbarzadeh, 2021; Souza and Jaber, 2024). The Inventory Discrepancy Index (IDI) declined from 25.0% to 18.0%, equivalent to a 28.0% reduction. The largest change was observed in the Obsolescence Rate, which fell from 7.9% to 3.6%, corresponding to a 54.6% reduction. In addition, the model achieved a Forecast Accuracy of 79.0%, introducing a structured forecasting capability that was not available in the initial system. Overall, the graphical comparison shows a clear improvement across the evaluated indicators.

5.3 Proposed Improvements

Figure 4 shows the current process (AS IS), while Figure 5 presents the improved process (TO BE) after the implementation of the proposed model.

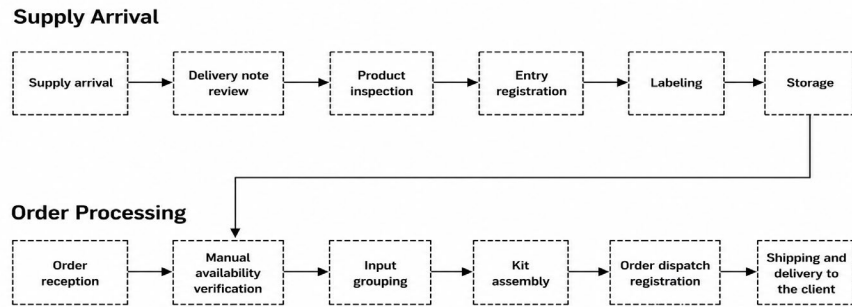


Figure 4. AS IS model representation

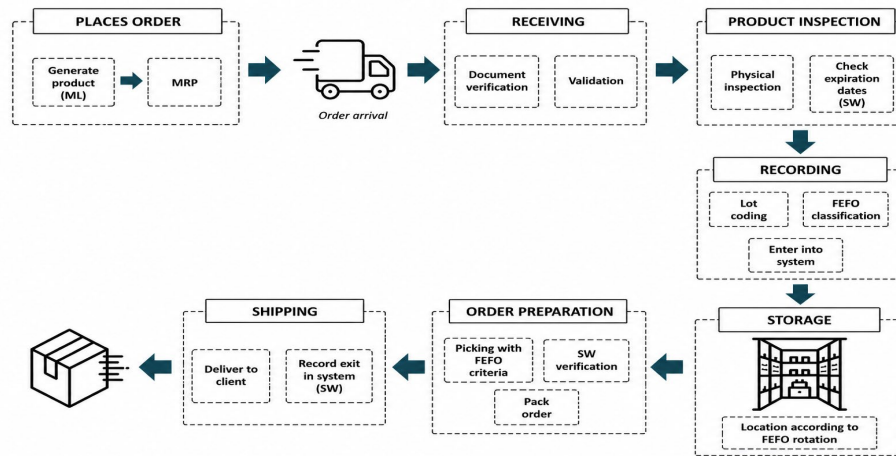


Figure 5. Representation of To Be model

Table 5 presents the comparison between the initial, expected, and achieved results.

Table 5. Results comparison before and after model implementation

Indicator	As is	Expected target	Achieved result
Inventory Stockout Index (ISI)	5.7	< 5%	3.4%
Inventory Discrepancy Index (IDI)	25%	21.5%	18%
Forecast Accuracy	-	0.75	79%
Obsolescence Rate	7.2%	4.9 %	3.6 %

The initial state of the system, the expected target values defined during the design phase, and the final results obtained after the implementation of the proposed model are compared in Table 5. This comparison enables the evaluation of system performance against the improvement targets established based on bibliographic references and technical design criteria.

Regarding the Inventory Stockout Index (ISI), the objective was to reduce the indicator to values below 5.0%. The achieved result of 3.4% not only met but exceeded this target. For the Inventory Discrepancy Index (IDI), the expected value was 21.5%, while the final result reached 18.0%, indicating a greater reduction than initially projected.

In terms of Forecast Accuracy, the target value was set at 75.0%, whereas the proposed model achieved 79.0%, demonstrating an improvement in demand prediction performance. Similarly, the Obsolescence Rate was expected to decrease to 4.9%; however, the final result reached 3.6%, reflecting a significant reduction in obsolete inventory.

Overall, these results indicate that the proposed model successfully achieved and surpassed the expected improvement targets across all evaluated indicators, confirming its effectiveness in enhancing inventory management performance.

5.4 Validation

The proposed model was validated through a hybrid approach combining field testing and discrete-event simulation, allowing both operational feasibility and statistical reliability to be assessed.

The validation stage was designed to evaluate the proposed model under both real and simulated conditions. Historical operational data obtained from the company were used to develop the forecasting model, estimate inventory parameters, and define the inputs required for the simulation environment. Therefore, the field implementation and the simulation model were not independent activities but complementary stages within a unified validation framework.

First, a pilot test was conducted for the Machine Learning (ML) and Standard Work (SW) components using real company data from 2022–2025. This stage confirmed that the forecasting model aligns with historical demand patterns and that standardized procedures reduce variability in warehouse operations. The results obtained during the pilot implementation, including forecast accuracy and operational performance data, were subsequently used to calibrate the simulation environment.

Second, a discrete-event simulation model was developed in Arena to represent the supply and distribution processes of surgical kits. Two scenarios were analyzed: the current (As-Is) and the improved (To-Be), which integrates ML, MRP, Standard Work, and FEFO. Input parameters were defined using statistical distributions derived from historical data, including demand, interarrival times, and processing times. In this way, the simulation model was directly supported by operational evidence collected during the pilot stage, enabling the evaluation of the MRP and FEFO components under different replenishment and inventory rotation scenarios. The simulation was executed with 90 replications at a 95% confidence level, ensuring robust comparisons between scenarios. The model structure is illustrated in Figure 6.

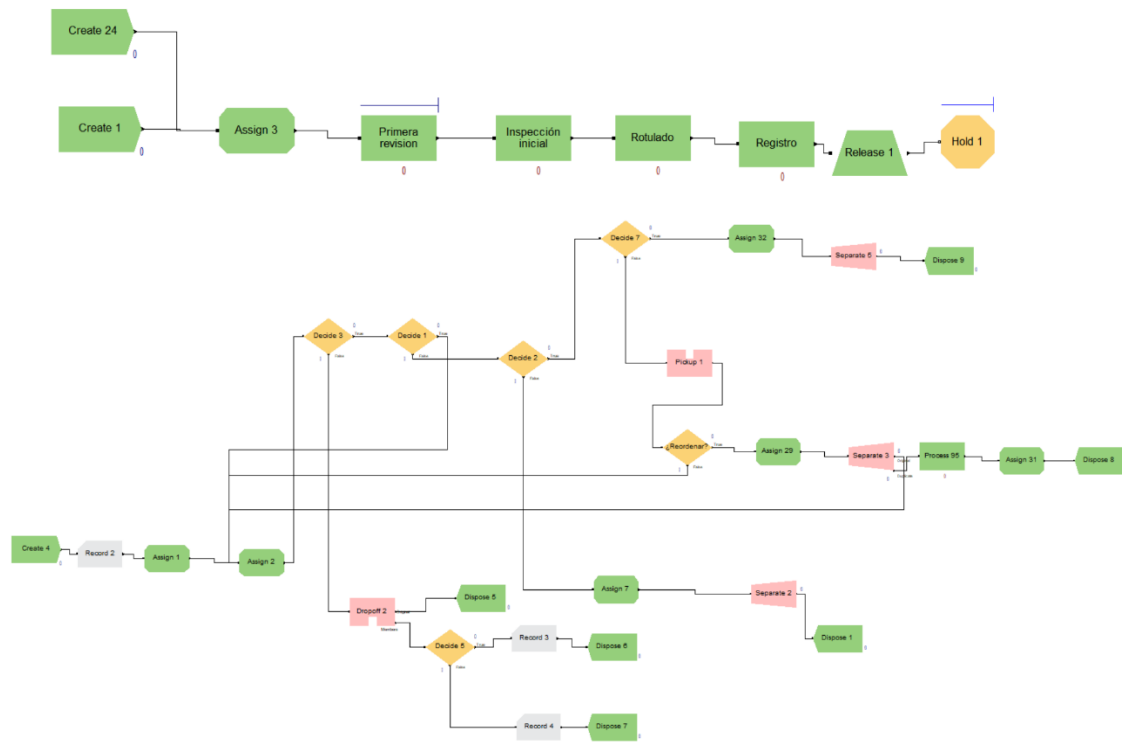


Figure 6. Simulation model

Results show that the Stockout Index (ISI) decreases from 0.0577 to 0.0343, representing a 40.6% reduction. A paired t-test confirmed the statistical significance of this improvement ($p < 0.05$), with a mean difference of -0.0234 and a 95% confidence interval between -0.0379 and -0.0089 . Additionally, the validation of the base model shows that the simulated ISI confidence interval (0.0462–0.0693) contains the observed value (0.0565), indicating that the model accurately represents real operating conditions.

6. Conclusion

This study successfully achieved its main objective by designing, implementing, and validating an integrated inventory management model to reduce stockouts in a medical-surgical supply chain. The results show a significant reduction in the Stockout Index (ISI), from 5.77% to 3.43%, representing a 40.6% improvement in product availability.

The findings indicate that stockouts are caused by the interaction of planning, execution, and control deficiencies. In this context, the integration of demand forecasting, MRP, Standard Work, and FEFO proved to be an effective and complementary solution, improving replenishment accuracy, reducing variability, and strengthening inventory control.

Additionally, the model achieved a forecast accuracy of 79%, contributing to the reduction of the Inventory Discrepancy Index (IDI) from 25% to 18% and decreasing product obsolescence, reflecting better alignment between physical and system inventories.

From an operational perspective, Standard Work reduced process variability, FEFO improved inventory rotation, and MRP enabled more structured and data-driven replenishment decisions.

Overall, the results confirm that the proposed model is effective, practical, and scalable, as it can be implemented with low-cost tools. This research also contributes to the literature by showing that integrating predictive analytics with operational tools significantly improves inventory performance and reduces stockouts in healthcare supply chains.

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Biographies

Javier Miguel Castillo Tejada is a faculty member and research advisor at Universidad de Lima, Peru. His work focuses on industrial engineering and operations management, and he has supervised undergraduate research projects related to process optimization and supply chain management.

Gustavo Adolfo Luna Victoria León is a faculty member and research advisor at Universidad de Lima, Peru. His academic work is related to industrial engineering and operational systems, with experience in supervising research projects focused on logistics and process improvement.

Melany Ramirez Tapia is an Industrial Engineering student at the Universidad de Lima, Peru, currently in her final year with a specialization in business engineering. She has professional experience in commercial and organizational environments, with a strong focus on data analysis, performance evaluation, and process improvement. Her experience in commercial management, data-driven analysis, and process optimization has contributed to this research by supporting the evaluation and improvement of operational processes related to inventory control and replenishment systems.

Samantha Xiomara Reyes Ramirez is a Staff in Assurance at EY Perú. She is an Industrial Engineering graduate from Universidad de Lima, Peru, with a specialization in technological innovation. She has experience in compliance audits and consulting projects focused on Anti-Money Laundering and Counter-Terrorism Financing (AML/CFT), Corporate Criminal Liability Models, and Anti-Bribery Management Systems (ISO 37001). Her experience in data analysis and process improvement for decision-making, along with her use of analytical tools such as Excel and Power BI, has supported her contribution to this research, particularly in the structuring and analysis of data for improving inventory management and reducing stockouts.