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Implementation of Process Standardization and Demand Forecasting to Increase Inventory Turnover in a Peruvian Textile Company

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Abstract

In recent years, Peruvian textile companies have faced challenges associated with demand variability and lack of control over inventories. These problems generate cost overruns and stock shortages, affecting operational efficiency. In this context, improving inventory management and having standardized processes is essential to maintaining competitiveness. Given this need, an improvement model based on forecasting techniques and process standardization is proposed, with the aim of optimizing turnover in a Peruvian textile company. The model was validated through discrete-event simulation and an operational pilot test, allowing the real impact of the tools applied to be evaluated. The results confirm important findings: inventory turnover increased from 2.0 to 4.3 times per year, inventory record accuracy increased from 78% to 95%, and forecasting error was reduced from 47% to 12%. These achievements demonstrate that the proposed model can generate sustainable and replicable improvements in similar textile companies.

Keywords
Inventory management, demand planning, process optimization, fashion industry.

1. Introduction
Inventory management and demand variability represent persistent operational challenges in the textile and apparel industry due to short product life cycles, seasonal demand, and production complexity. Under these circumstances, the textile and apparel sector is one of the most important manufacturing activities in the Peruvian economy, contributing S/ 5.246 billion soles to GDP and experiencing a compound annual growth rate of 8% between 2020 and 2024, as reported by Produce (2025). However, the sector continues to face conditions that limit its performance, including high levels of informality, low technology adoption, and highly fluctuating demand, factors that hinder production planning accuracy and inventory control performance. The General Office of Impact Assessment and Economic Studies of Produce (2025) indicates that this industry generates more than 448,000 jobs and reports that only 23% of these are formal jobs, which directly impacts productivity and the ability to optimize logistics processes. These characteristics justify the importance of conducting research to strengthen inventory management in Peruvian textile companies.

Various authors have proposed analytical and operational tools to address these challenges. Giri and Chen (2022) demonstrated that forecasting models increase demand accuracy and reduce inventory obsolescence. In addition, Yasir et al. (2022) demonstrated that integrating external variables can increase forecast accuracy by up to 25%. For their part, Svetunkov et al. (2023) highlight that state space models are suitable for irregular demand, while Bizuneh and Omer (2024) emphasize that process standardization helps reduce errors and improve operational traceability. Although these approaches have shown positive results, they are often applied independently, which limits their impact in environments where inventory management depends on coordination between forecasting, planning, and operational execution.

The selected case study reflects this operational need. The analyzed company has an inventory turnover of only twice a year, well below the industry average of 5.7 times, according to the Instituto Nacional de Estadística e Informática (2021), representing a technical difference of 3.7 times. This performance can be explained by three main causes: the absence of a demand forecasting model that allows for adequate anticipation of required volumes, production delays that cause late deliveries of the finished product and affect availability, and significant gaps between what is found in the physical inventory and the information reflected in the system. These conditions limit consistent operational planning and prevent the maintenance of optimal inventory levels. Therefore, the hypothesis arises that the integration of forecasting models and process standardization can significantly improve inventory turnover in a Peruvian textile company. Based on this, the central research question is formulated: How does the integration of demand forecasting and process standardization impact inventory turnover in a Peruvian textile company?

Based on this hypothesis, the content of the study is structured as follows: Section 2 presents the literature review, Section 3 outlines the methodology adopted, Section 4 details the data collection process, and Section 5 shows the results together with the validation of the model, while Section 6 develops the final conclusions of the work.

1.1 Objectives

- To evaluate the impact of integrating demand forecasting and process standardization on inventory turnover.
- To reduce demand forecasting error using exponential smoothing statistical models in a textile company.
- To increase inventory record accuracy through warehouse process standardization and finished goods registration controls.

2. Literature Review

2.1 Inventory Control and Optimization Strategies

Inventory management is a key element in ensuring product availability, reducing stockouts, and avoiding accumulations that affect turnover in textile companies. Olvera et al. (2025) developed a model based on LQR control that adjusts inventory levels in response to variations in demand, while Conceição et al. (2021) demonstrated that combining ABC analysis and reorder points improves replenishment in footwear companies. In the textile sector, Milojević et al. (2021) and Zheng and Chen (2024) showed that integrating ABC classification with forecasting models allows for more accurate ordering and reduces excess inventory. In addition, seasonality directly influences replenishment patterns (Shakila et al. 2020), and collaborative policies such as VMI and consignment can reduce total costs by up to 14.8% (Lotfi et al. 2023). However, most studies analyze inventory management in isolation, without considering its relationship to other processes such as forecasting or planning. This lack of connection limits the real impact of the proposed solutions, which is why this study proposes a more integrated approach that combines these tools to improve operational results.

2.2 Demand Forecasting Methods under Uncertainty

One of the key elements in this integration is demand forecasting, as it allows us to anticipate needs and make more accurate decisions in contexts where consumption patterns are constantly changing. In the textile sector, for example, seasonality, short life cycles, and variability in trends make predicting demand a challenge. Giri and Chen (2022) reported 18% improvements in forecast accuracy, while Yasir et al. (2022) achieved 25% increases by incorporating external variables such as weather and social preferences. In more dynamic contexts, Swaminathan and Venkitasubramony (2023) highlight that artificial intelligence allows patterns to be identified in real time and enables a response to sudden changes in demand. Although traditional methods such as Holt-Winters and ARIMA remain effective (Kačmáry and Lörinc 2023), recent studies propose more flexible approaches such as State Space, Svetunkov et al. (2023), or techniques based on Google Trends and machine learning (Tsao et al. 2023). Despite these advances, many models are applied in isolation, without connection to tools such as standardized operational processes.

Therefore, this work proposes a more direct integration between forecasting and planning, in order to strengthen decision-making and reduce uncertainty in highly variable production environments.

2.3 Operational Standardization and Inventory Reliability

In addition to demand planning, process standardization plays an important role in improving inventory turnover, as it reduces recording errors and ensures reliable data for decision-making. Bizuneh and Omer (2024) applied Value Stream Mapping to simplify workflows and eliminate non-value-adding activities, while Akkerman et al. (2024) developed systematic inspection mechanisms that reduce differences between physical and accounting inventory. Chehrazi (2025) showed that transaction errors and invisible losses increase when there are no clear recording protocols, and Argun and Alptekin (2023) together with Chong et al. (2022) used anomaly detection and deep learning techniques to improve data consistency. Although these studies show improvements in information quality, most do not directly link standardization to processes such as forecasting or master planning. This disconnect reduces the potential for improvement in comprehensive management, so this study proposes incorporating standardization as a basis for strengthening the accuracy of forecasting.

3. Methods

The methodology integrates the study design, population definition, sampling, instruments, and data collection procedures. The population consisted of the company's historical records between 2021 and 2024, and the units of analysis varied according to each component of the model: the batches entering the warehouse for the inventory record study and monthly sales for the forecasting model.

In this study, the dependent variable is inventory turnover, understood as the performance that the proposed solution seeks to improve. The independent variables are organized according to each phase of the model: standardization of inventory recording and accuracy of demand estimation. These variables are used to derive the operational indicators used to evaluate the impact of the model, which are presented in Table 1. Similarly, for the standardization phase, sampling for finite populations was applied, obtaining a sample of 64 batches with 95% confidence and 5% error, which allowed for the evaluation of the variability between physical and recorded inventory. In the forecasting phase, an ABC analysis was used to select the lines with the greatest impact on demand, and monthly sales were consolidated as input for the statistical model. Data collection was carried out through physical counts, document review, ERP extraction, and statistical processing in Excel and RStudio, ensuring consistency and traceability at all stages of the study.

With the unit of analysis previously defined, we proceed to describe the solution model developed to address the opportunities for improvement identified in the diagnosis. The structure presented in Figure 1 allows us to intervene on the factors that directly affect inventory turnover: recording and estimating demand. Phase 1 standardizes the inventory recording process to reduce errors, improve the accuracy of information, and ensure product traceability. Phase 2 applies a forecasting model based on the state space approach, with the aim of projecting demand more accurately and reducing variability in supply. This model allows for an orderly and measurable evaluation of how each phase contributes to improving the company's inventory turnover. The application of each phase is described below.

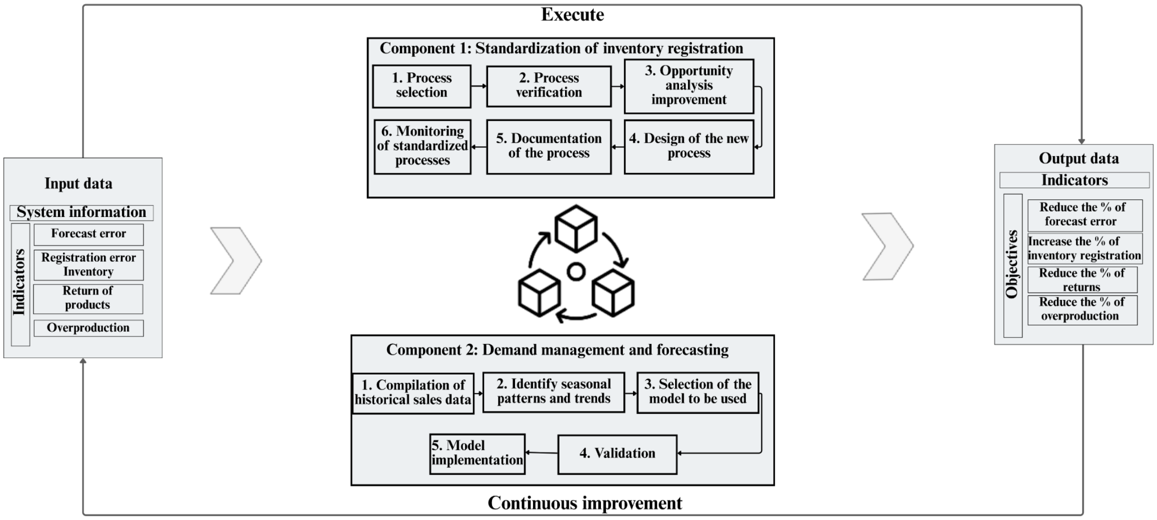


Figure 1. Proposed solution model

Phase 1: Standardization of inventory records

Phase 1 focuses on improving the recording of finished product inventory, given that significant differences were found between physical inventory and what was recorded in the system. Figure 2 shows a real case of stock stored without being entered into the system, where returns remained unrecorded for between 3 and 9 months. This affected actual availability, delayed replenishment, and led to an accumulation of units that were not visible for planning purposes. To confirm the magnitude of the problem, physical counts were performed, guides were reviewed, and comparisons were made with the ERP, identifying delays in data entry, errors in entering units, and incomplete records.

Based on these findings, a new standardized process was designed that clearly defines activities from receipt, counting, and recording of products, including returns. The flow incorporates visual controls, defined responsibilities, and the use of the "Units in transit" category to record garments as soon as they are received. In addition, a deadline of 1 to 5 days was established to ensure that the ERP is updated in a timely manner and to prevent the physical inventory from falling out of sync with the system. The standardized procedure was summarized in a visual diagram that guides its correct application. Figure 3 presents this flow, where activities are ordered from receipt to final registration of garments. Subsequently, finishing, returns, and warehouse personnel were trained in the correct execution of the procedure, reinforcing the importance of recording information within the established deadlines. Finally, biweekly monitoring was established through internal audits and checklists to ensure compliance with the standard and keep the inventory recorded in the system aligned with the actual stock.

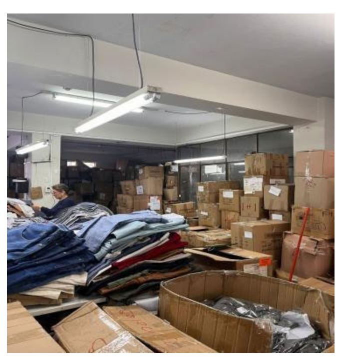


Figure 2. Stock stored without entering the system

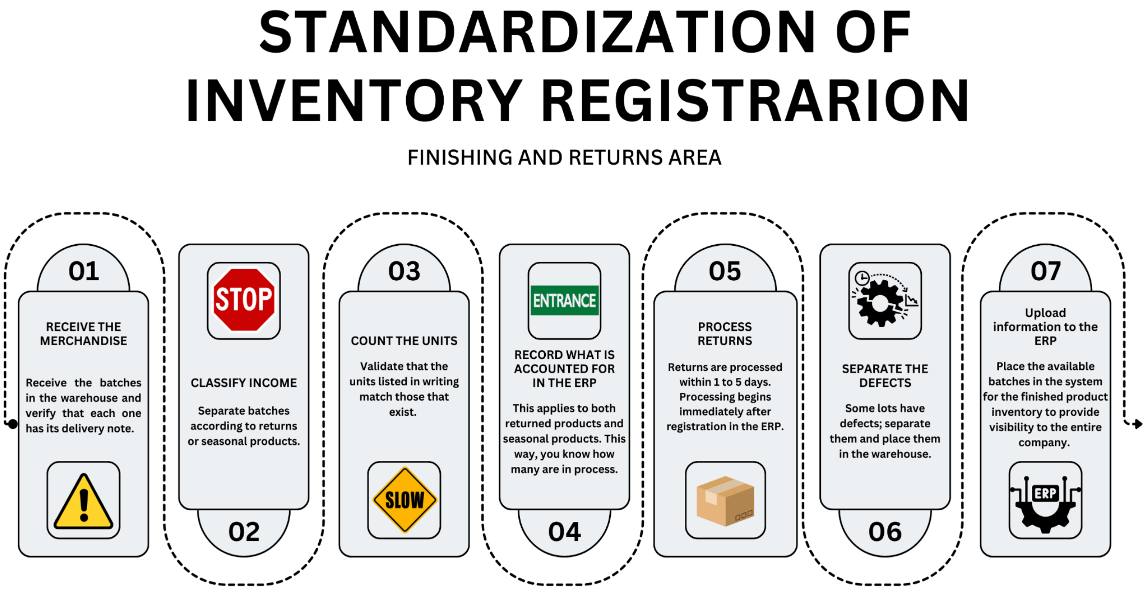


Figure 3. New standardized process

Phase 2: Demand management and forecasting

In this second phase, the forecasting model was developed, which serves as the main basis for production planning. To do this, historical sales data for the years 2021–2024 was first consolidated, integrating the files managed by channel, brand, and line, and correcting duplicate or inconsistent records. With the unified information, the behavior of the line representing more than 60% of sales was analyzed, identifying trends and seasonality, such as the recurring increase in April and December and the drop in May associated with low stock availability. This analysis allowed us to understand the actual patterns of demand and define which elements the statistical model should capture. Next, different forecasting approaches were evaluated, such as ARIMA, Holt-Winters, and Exponential Smoothing in State Space (ETS), considering their fit to the historical series and their ability to represent the identified seasonality. Due to the marked seasonal structure and monthly variability, the ETS model was selected as the main option. Validation was performed in RStudio using a training and testing partition, using the Mean Absolute Percentage Error (MAPE) as an accuracy indicator, defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{(D_i - \widehat{D}_{i})}{D_i}\right| x\ 100$$

Where D_i represents actual demand and $\widehat{D}_i$ represents forecasted demand. The model obtained an average MAPE of 9.76%, showing a good fit to recent data. Figure 4 shows the graph of the 2025 forecast generated with the ETS model, which breaks down the time series into error, trend, and seasonality. This approach was chosen for its ability to adapt to irregular patterns and update parameters as new data is incorporated. Finally, an implementation plan was designed that includes training sessions for the sales team, which is responsible for managing demand. These sessions allow the model's results to be interpreted, its impact on planning to be understood, and its proper use in decision-making to be ensured. With this phase, the company now has a validated forecast and staff trained to use it as support for future planning.

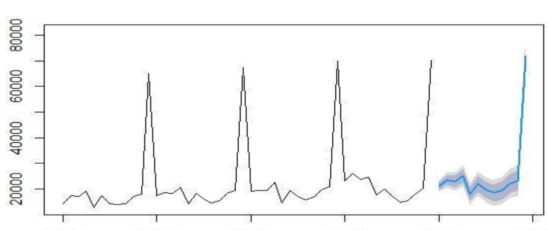


Figure 4. Demand forecast for 2025

Figure 5 presents the proposed implementation flow according to the proposed model: process standardization, demand management, and forecasting. Each stage includes operational activities, decision points, and feedback cycles that allow results to be validated and iterative adjustments to be made. In the first stage, procedures are formalized through documentation and training to ensure uniformity. In the second stage, the Exponential Smoothing in State Space (ETS) model is applied, which explicitly combines the components of error, trend, and seasonality to generate forecasts based on historical data and reduce estimation error.

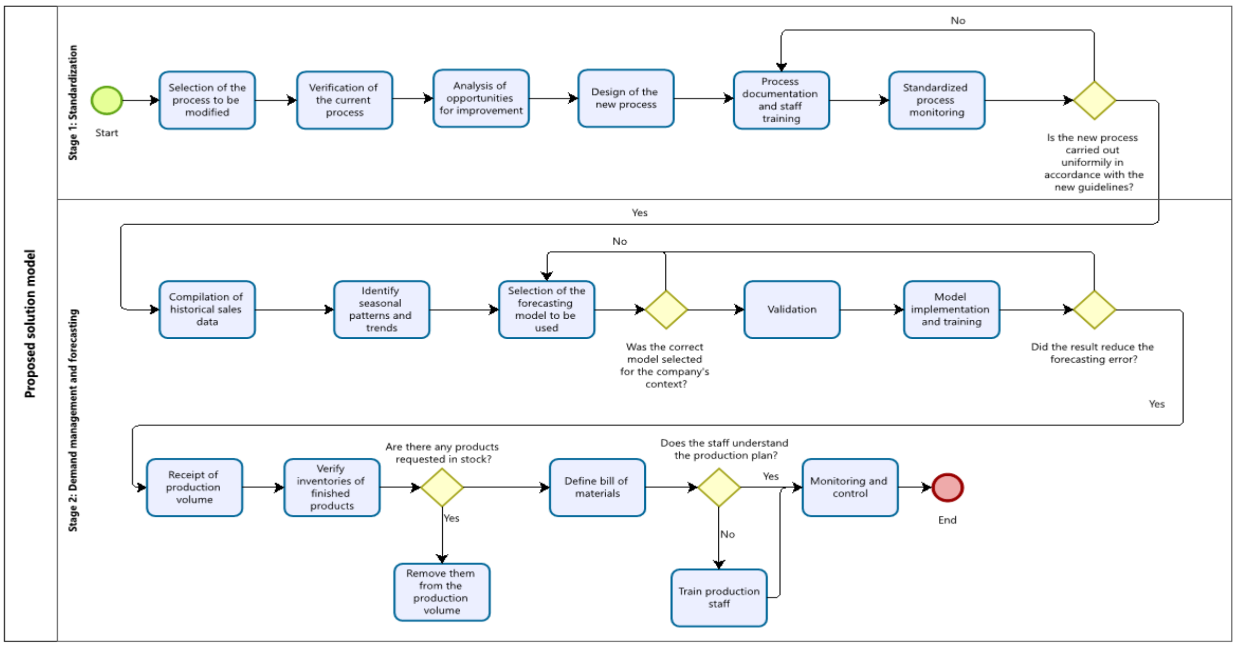


Figure 5. Model implementation flowchart

To evaluate the performance of the proposed model, the indicators shown in Table 1 were defined, which allow for measuring improvements in record accuracy, forecast precision, and compliance with the production plan.

Table 1. Process indicators

Indicator	Objective	Formula	Objective
Inventory turnover	Increase current inventory turnover	$\frac{Cost\ of\ sales}{Average\ inventory}$	Turnover ≥ 4 veces
Mean absolute percentage error	Improve demand forecast accuracy	$\frac{1}{n}\sum_{i=1}^{n} \Vert \frac{D_i - D_f}{D_i} \Vert\ x\ 100$	MAPE $< 15\%$
Inventory registration rate	Increase inventory registration rate	$\frac{Registered\ units}{Physical\ units}\ x\ 100$	Rate ≥ 95%

4. Data Collection

Data collection for this study was based on historical information from the database obtained by the company's sales team, inventories, and ERP, where physical inventory records, production reports, and shipping reports for the year 2024 were requested. These constitute the most representative source for analyzing the actual behavior of the logistics and production process. Twelve months of data on sales, returns, initial and final inventories, labor availability, processing times, and variations between physical and accounting inventory were consolidated, which made it possible to identify gaps such as differences of up to 32% between reported inventories and delays in updating records.

Likewise, historical demand databases were collected for the most representative lines (shirts, jackets, and shorts), which were later used to develop the forecasting model, as well as operational information related to cycle times for receiving, accounting, labeling, packaging, and ERP loading activities, which was necessary for building the simulation model. All information was organized and validated, eliminating duplicate records, unifying formats, and comparing ERP data with inventories collected in the field. Likewise, the Capstone methodology guidelines were followed to ensure reliability and consistency. This process made it possible to structure a robust basis for evaluating current performance, feeding into forecasting models, and supporting the As Is and To Be comparisons required for methodological validation of the study.

5. Results and Discussion

5.1 Numeral Results

The empirical validation of the improvement model is confirmed by analyzing the key performance indicators (KPIs) derived from the simulation of the To Be scenario and the implementation of support tools. The results demonstrate full compliance with the objectives set. The primary indicator on which the research focuses, Inventory Turnover, increased from 2.0 to 4.0 times per year, which translates into a 2.0-fold improvement and confirms the achievement of the objective. This finding provides empirical evidence that the integrated methodology contributes to improving working capital utilization and reducing stock immobilization in the textile company.

Efficiency in inventory management was based on superior predictive planning and increased reliability of the data used. The implementation of the exponential smoothing forecasting model resulted in a 35 percentage point reduction in the Mean Absolute Percentage Error (MAPE), falling from 47.5% in the baseline to 12.5% in the improved model. This value exceeds the 15% target and positions the company's predictive capacity at a high reliability threshold. Thus, the application of Standard Work for recording and operational control increased Inventory Recording Accuracy from 80% to 96%, exceeding the 95% target and ensuring that the information used for decision-making is reliable.

In summary, these results show a clear improvement in inventory performance driven by better forecasting and data accuracy. As shown in Table 2, all indicators improved significantly, particularly MAPE, which decreased by 35 percentage points, reflecting a substantial increase in forecasting accuracy. This evidence confirms that enhanced demand prediction plays a critical role in optimizing inventory performance. Therefore, the integration of operational standardization with data-driven forecasting tools emerges as a high-impact strategy for achieving greater efficiency and responsiveness in textile supply chain management.

These results show that improving forecasting accuracy alone is not enough if inventory data is unreliable. Integrating both elements allows for better decision-making and a more effective response to demand variability.

Table 2. Process indicators before and after the improvement was implemented

Indicator	Unit	Base Model	Improved Model	Gap (Improvement)
Inventory Turnover	times	2	4	2
Inventory registration rate	%	80	96	16
MAPE	%	47.5	12.5	35

5.2 Graphical Results

This section presents the graphical results of the forecasting model, allowing for the analysis of MAPE evolution across product lines and the identification of relevant demand patterns. Figure 6 illustrates the monthly evolution of MAPE by product line. Shirts show a reduction in forecasting error until March, followed by a slight increase in April. Jackets exhibit greater variability, with peaks in February and May, while T-Shirts present a gradual increase in error between January and April. Shorts display mixed behavior, with a significant peak in April and a notable decrease in May.

Overall, forecasting accuracy improves in the initial months due to better alignment between the model and demand patterns. However, later fluctuations suggest the need for periodic recalibration to maintain accuracy over time.

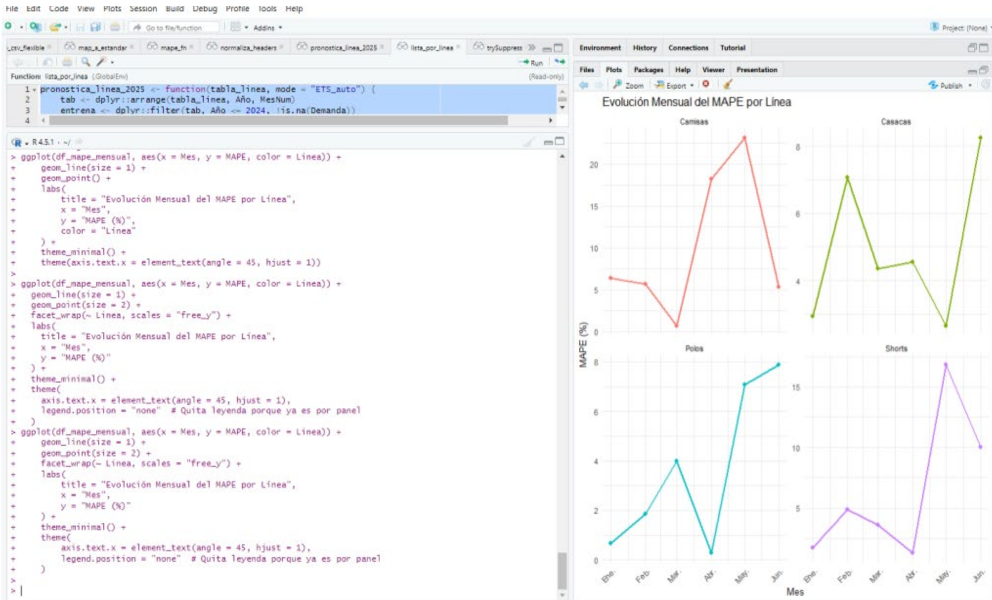


Figure 6. Monthly evolution of MAPE by product line

Figure 7 shows the behavior of final inventory levels following the implementation of the forecasting model. A sustained reduction is observed throughout most of 2025, which can be attributed to improved demand forecast accuracy. By reducing forecasting errors, planned production volumes are better aligned with actual demand, minimizing overproduction and reducing the accumulation of obsolete inventory. This behavior highlights the impact of forecasting accuracy on improving inventory control over time.

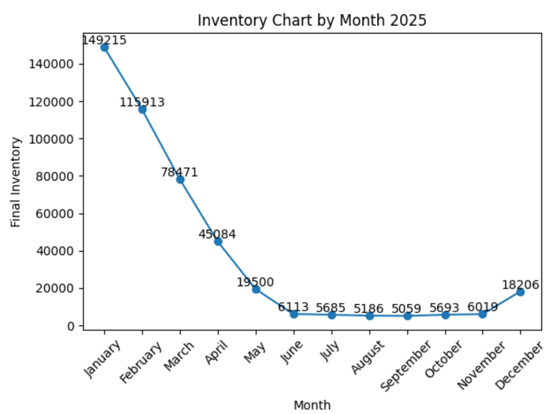


Figure 7. Inventory behavior after accurate demand forecasting

Figure 8 shows the overall impact of the integrated model by comparing the magnitude of improvement across key performance indicators. The results highlight which indicators experienced the most significant changes and how they are related within the case study.

These findings show that improvements in data accuracy and operational processes work together to strengthen inventory management performance, highlighting that the combined improvement of forecasting accuracy and data reliability drives stronger inventory performance.

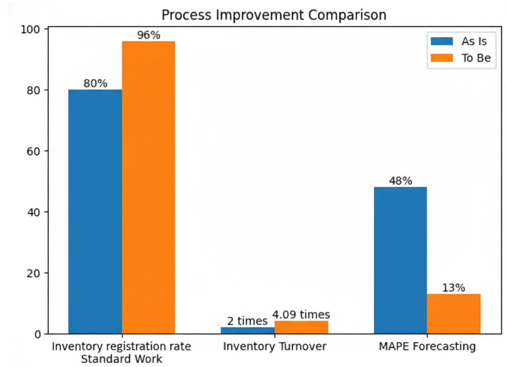


Figure 8. Variation in Indicators before and after the Improvement

These findings are consistent with previous studies such as Giri and Chen (2022), which highlight the importance of forecasting accuracy in reducing inventory inefficiencies. However, this study shows that integrating forecasting with process standardization generates a greater impact on overall inventory performance, improving both demand estimation and data reliability.

5.3 Proposed Improvements

The improvement proposal aims to address the root causes of low inventory turnover identified in the diagnosis: returns not recorded on time, inaccurate forecasts, and late delivery of finished products. First, the inventory recording process in the finishing, finished products, and returns area was redesigned, incorporating the immediate recording of garments in the ERP under the category "Units in transit," a standard period of 1 to 5 days to complete the system update, and the use of visual formats and checklists. These improvements were reinforced with staff training and a biweekly monitoring scheme to ensure that returns do not remain invisible to planning for months and that the information in the system reflects the actual available stock.

Secondly, a demand forecasting model was developed using the Exponential Smoothing in State Space (ETS) approach implemented in RStudio, based on the consolidation and cleansing of the 2021–2024 historical series. This process included the integration of scattered databases, the identification of seasonal patterns such as recurring increases in April and December and declines associated with stock shortages, as well as the comparison of different models to select the one that best represented the actual dynamics of demand. To ensure that the results are used effectively in planning, a training plan was designed for the commercial area so that the forecast is routinely incorporated as a strategic resource that guides decision-making and not just as an isolated exercise, thus facilitating continuous alignment between projected demand and planned production.

5.4 Validation

The model was validated using a hybrid approach that combined the pilot test with the discrete simulation in Arena shown in Figure 9, allowing for a comparison of the performance of the indicators before and after implementation. First, the forecast error (MAPE) was reduced from 47% to 12%. Compared to previous studies such as Giri and Chen (2022), which report forecast accuracy improvements of up to 18%, the proposed model achieved a higher level of predictive performance, while also meeting the recommendation of Chen and Lu (2021), who point out that values below 15% represent high levels of accuracy in the fashion industry. Likewise, inventory record accuracy increased from 78% to 95%, in line with the ranges reported by Martín et al. (2019) for standardized processes. Finally, inventory turnover increased from 2.0 to 4.3 times, falling within the values reported for the textile sector (Kwak, 2019).

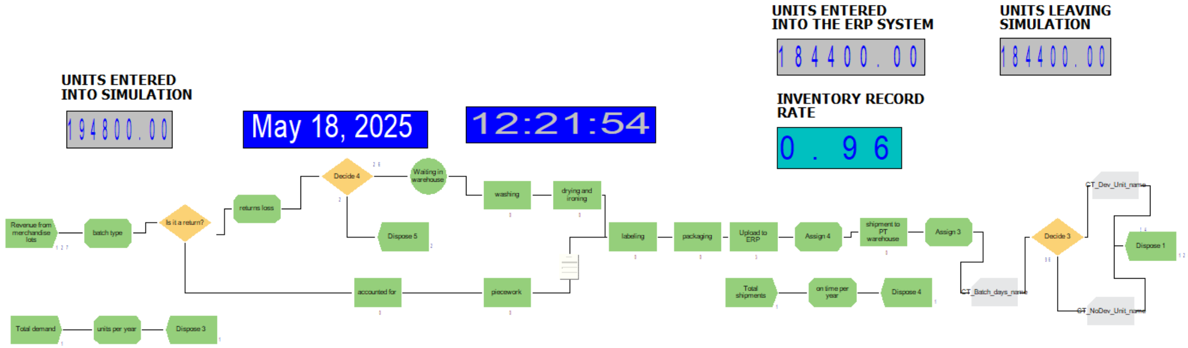
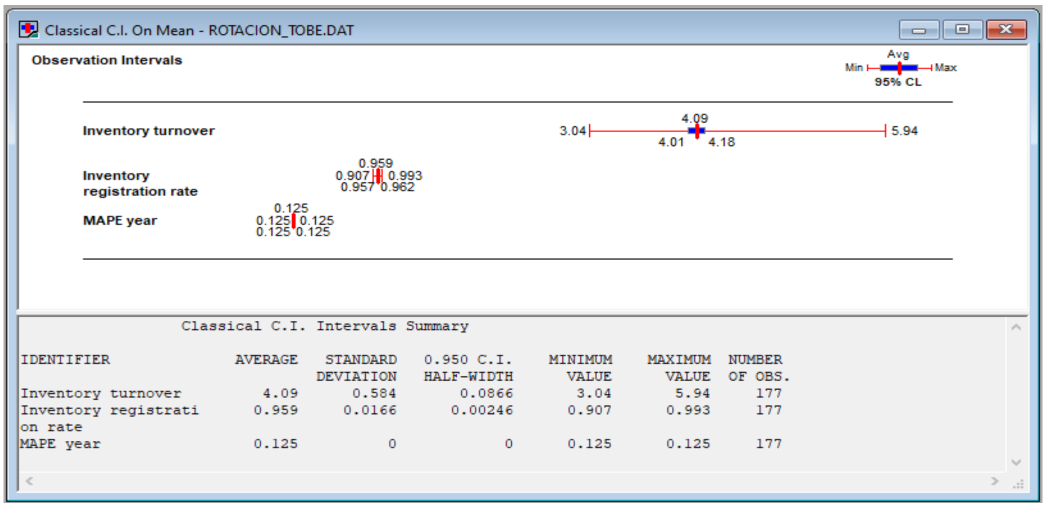


Figure 9. Simulation in Arena

Figure 10 shows the 95% confidence intervals obtained using Arena for the improved indicators, confirming the statistical stability of the model and the consistency of the results obtained.



IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
Inventory turnover	4.09	0.584	0.0866	3.04	5.94	177
Inventory registrati on rate	0.959	0.0166	0.00246	0.907	0.993	177
MAPE year	0.125	0	0	0.125	0.125	177

Figure 10. Indicators and confidence intervals of the improved model

5.5 Advanced Forecasting Approaches under Demand Uncertainty

The results obtained with the ETS model confirm that statistical forecasting can significantly improve planning accuracy in environments characterized by high demand variability, reducing forecasting error from 47% to 12%. However, demand behavior in the textile industry is influenced by dynamic factors such as seasonality, market trends, and changing consumer preferences, which may generate nonlinear patterns over time.

Under these conditions, future implementations of the proposed model could explore hybrid forecasting approaches that combine ETS with Artificial Intelligence (AI) or Machine Learning (ML) techniques, enabling the model to adapt more effectively to complex demand patterns and potentially achieve further improvements in inventory turnover and production planning performance.

6. Conclusion

This study shows that integrating forecasting and operational improvements can significantly enhance inventory performance in a textile company operating under demand variability and operational inconsistencies. The results indicate that inventory turnover increased from 2.0 to 4.3 times per year, supported by improvements in forecast accuracy (MAPE reduced from 47% to 12%) and inventory record reliability (from 78% to 95%). These results show that coordinated operational and analytical interventions can strengthen logistics performance and reduce stock immobilization.

The main contribution of this research lies in proposing an integrated operational model that simultaneously addresses forecasting accuracy and inventory data reliability, two factors frequently studied independently in previous literature. By combining these dimensions, the model offers a structured approach that can be adapted to textile companies with similar operational characteristics. However, this study is limited to a single-company case and relies on historical data from a specific operational context. Therefore, the generalizability of the results should be interpreted with caution.

Future research may explore the use of alternative forecasting approaches, including ARIMA and hybrid machine learning models, to further enhance predictive performance. While the ETS model proved effective in this study, demand behavior in the textile sector is often highly variable and difficult to fully capture using traditional statistical methods. In this sense, more advanced approaches could provide greater flexibility to represent complex demand patterns and improve forecasting accuracy. This, in turn, could strengthen decision-making processes and contribute to a more efficient and responsive inventory system. Additionally, future studies could examine the integration of forecasting tools with ERP systems and production planning processes, as well as validate the proposed model in different industrial contexts.

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