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Original Article

An Integrated Lean and Machine Learning Approach to Inventory Management in Automotive Accessories SMES

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Abstract - *In the Peruvian automotive accessories sector, low inventory turnover is a critical problem that hinders operational efficiency, increases storage costs, and reduces liquidity. This study aims to design and validate an integrated inventory management model to improve stock turnover in an automotive accessories warehouse. The model combines ABC classification, Economic Order Quantity (EOQ), slotting, 5S methodology, and machine learning-based demand forecasting. The methodology includes a systematic literature review, problem diagnosis, tool integration, simulation in Arena software, and pilot implementation. Key results revealed a 33.43% improvement in inventory turnover, a 30% reduction in average inventory, a 60% decrease in picking time, and a 19.95% reduction in total logistics costs. Additionally, the study achieved an 18.5% improvement in Inventory Record Accuracy (IRA) and a 22.69% increase in Location Record Accuracy (LRA). These findings highlight the effectiveness of integrating lean and technological tools in enhancing inventory management in automotive accessories warehouses. The study addresses a research gap in Latin America and offers a replicable model that contributes to improving operational efficiency and sustainability in similar industrial contexts.*

Keywords - *Inventory management, Stock rotation, Machine learning, Multi-criteria ABC, PYME, 5S, Slotting, Kardex.*

1. Introduction

In the current landscape, organizations are motivated to implement more dynamic and effective processes that drive their expansion and evolution [1]. Thus, there are many theories about the next phase of logistics development. Many logistics experts believe that collaborative logistics-logistics models built with continuous, real-time optimization and communication between all supply chain partners-will be the next phase of evolution [2]. According to recent data from ComexPerú, in Peru, microenterprises represent 95.6% of all businesses, small businesses 3.8%, and medium-sized businesses 0.1%. This sector is predominantly focused on activities related to services (47%), trade (36%), and production (14%). Nationally, Lima accounts for 11.5% of the country's Micro and Small Enterprises (MSEs) [3]. According to the National Household Survey (ENAHO), MSMEs currently represent 96% of businesses in Peru and employ 43% of the Economically Active Population (EAP). In 2020, there was a 16.4 percentage point increase in the percentage of the EAP employed by MSMEs. MSMEs reported annual sales of S/ 107.945 billion, representing a 78.5% increase compared to 2020 and equivalent to 12% of the country's Gross Domestic Product (GDP). Despite this growth, the pandemic represented a devastating blow to MSMEs, especially in 2020, when one in two businesses closed. Although there was a 75% recovery in 2021, they are still below pre-pandemic levels, reflecting the sector's great vulnerability [4]. In this context, it is essential to promote measures that favor the growth and recovery of MSMEs. The primary problem addressed in this research is the low inventory turnover observed in a Peruvian SME, averaging only 3.31 times per year, which significantly lags behind the commercial sector's benchmark of 6.80 times. This underperformance generates excess stock, high storage costs, and low liquidity, underscoring the need for an integrated inventory management model.Specifically, a small company in the commercial sector dedicated to the sale of automotive accessories and spare parts was selected. With over 20 years in the market and headquartered in Lima, it has managed to consolidate its position thanks to its network of national and international suppliers from Brazil and China. One of the main challenges facing MSEs, including this company in the automotive sector, is supply chain management, where 66% of the country's companies have an incipient level of management. Regarding inventories, 71% of Peruvian companies report having up to 90 days of inventory, while the market standard suggests an average of 60.83 days at the 75th percentile [5]. Furthermore, the inventory turnover, a key indicator for evaluating management efficiency, in the analyzed company is 3.31 times, well below the 6.80 times ratio recorded in the commercial sector [6]. This indicator reflects a significant technical gap, generating a 94.84% opportunity for improvement. The economic impact of this inefficiency in terms of inventory and storage overruns amounts to 944,548.07 PEN, which represents approximately 13.95% of the average cost of sales over the last five years. To address these challenges, this research proposes an integrated inventory management model specifically designed for automotive accessories warehouses in Peruvian SMEs. The model integrates ABC classification, EOQ, slotting, 5S methodology, and Machine Learning-based demand forecasting to optimize stock turnover and enhance operational efficiency. By unifying these tools into a single framework, the model aims to improve inventory classification, reduce excess stock, and enhance warehouse layout and demand predictability.

This comprehensive approach represents a novel contribution to the literature, offering an effective solution to the problem of low inventory turnover in the automotive accessories sector in Peru. Although previous studies have explored the use of Lean Manufacturing tools such as 5S, ABC classification, and EOQ for inventory management, few have examined the integration of advanced forecasting methods like Machine Learning into warehouse management in automotive accessories SMEs.

Moreover, the existing literature largely neglects the combined application of these tools within a unified, integrated model specifically tailored to Peruvian SMEs' realities. This study addresses this research gap by developing and validating a comprehensive inventory management model that incorporates Machine Learning forecasting with Lean and supply chain management tools, thereby improving inventory turnover and overall operational efficiency in the automotive accessories warehouse context. Despite numerous studies on Lean manufacturing tools and inventory management, research that integrates machine-learning demand forecasting with multi-criteria ABC classification, EOQ, slotting, and the 5S methodology in the context of Latin American SMEs remains scarce. This gap is particularly evident in the automotive accessories sector, where low inventory turnover hampers operational efficiency and financial performance [6].

This study, therefore, addresses the problem of low inventory turnover-recorded at 3.31 cycles per year in the focal SME, compared with a benchmark of 6.80 [6]-by proposing and validating an integrated model that combines the aforementioned tools. The study's novelty lies in unifying Lean techniques and predictive analytics within a single framework and demonstrating its effectiveness through simulation and a pilot implementation. Following this introduction, Section 2 reviews the state of the art; Section 3 describes the proposed model and research methodology; Section 4 presents the validation and results; Section 5 discusses the economic and environmental evaluation; and Section 6 concludes the paper and suggests directions for future research.

2. State of the Art

In recent years, the integration of Lean Manufacturing principles with technological tools has emerged as a key strategy to address operational inefficiencies in inventory management, particularly in the automotive accessories sector of emerging economies. This literature review aims to synthesize the fundamental concepts and main contributions related to five critical methodologies: Economic Order Quantity (EOQ), 5S Methodology, Slotting, ABC Analysis, and Machine Learning.

These methodologies collectively form the foundation of the proposed integrated model, designed to improve Peruvian SMEs' inventory turnover and operational performance. The review of these thematic areas highlights the importance of balancing traditional inventory management practices with advanced forecasting techniques to achieve sustainable improvements. This integrative perspective provides the necessary framework to understand the evolution of inventory management models and underscores the novelty of incorporating machine learning into Lean-based strategies, addressing a significant research gap in the context of Peruvian companies and similar industrial sectors.

2.1. Economic Order Quantity (EOQ)

In inventory management, it is necessary to strike a balance between inventory holding costs and the benefits of maintaining it. As we know, having inventory ensures the availability of goods at all times. In this regard, the Economic Order Quantity (EOQ) model in inventory management determines the optimal order size and subsequently selects the supplier offering the lowest cost for that quantity. This helps minimize the total costs associated with inventory investment [7].

In a case study, the EOQ model was used with XYZ analysis through software technology to facilitate inventory strategy selection and spare parts inventory management in industrial, sales, and supplier companies [8]. The results were reflected in an optimal reorder point and improved cost management by reducing total storage and transportation costs. On the other hand, a case study about a company dedicated to the sale of automotive spare parts was used as a basis, in which it was discovered that the management of inventory and demand for spare parts is more critical than that of components used in the assembly of finished products, due to rapid technological innovations, time or responsiveness (due to the responsive product support process, 23% of spare parts become obsolete each year) and the demand for spare parts (which tends to show an irregular pattern) [9].

2.2. 5S Methodology

The increasing demand for next-day and even same-day deliveries has led to highly time-sensitive operations within warehouses. In this context, customer-initiated processes such as order picking have become particularly critical [10]. To address these operational challenges, the 5S methodology-a five-step approach aimed at promoting order and cleanliness in the workplace-has been widely implemented. This method has proven effective in enhancing business productivity. For instance, its adoption in a trading company led to the elimination of unnecessary items and the standardization of processes, resulting in a 26% increase in picking productivity and a more balanced warehouse operation [11].Accordingly, the 5S tool contributes to improved storage processes through better warehouse layout and organization. For example, it allows for the optimization of production time by ensuring order at workstations. As a result, the entire shop floor became more visible, leading to a highly efficient workflow [12]. Furthermore, in a case study conducted in the scaffolding manufacturing sector, the combined implementation of the 5S and SMED methodologies led to a 15% to 20% increase in production output [13].

2.3. Slotting

The slotting process aims to improve order picking by intelligently arranging products within the warehouse. Specifically, it involves the appropriate assignment of SKUs to available storage locations, determining the storage method, the amount of space to be allocated, and the precise location where each product should be stored [14]. A variety of strategies can be employed to optimize operations during location assignment. However, it is important to note that slotting can be particularly effective in addressing complex issues such as the Picker Routing Problem (PRP). In one case study, discrete Particle Swarm Optimization (PSO) was applied to solve a Vehicle Routing Problem with Waiting Time constraints (VRPWT). Techniques such as population initialization using the Push-Forward Insertion Heuristic (PFIH) were utilized.

As a result, the proposed method achieved a 30.9% improvement in efficiency compared to Ant Colony Optimization (ACO) when solving the routing problem [15]. In another case study, challenges related to system overload due to frequent replenishment demands were addressed through the development of an algorithm that explored the six degrees of freedom of a rigid body in three-dimensional space. This approach enabled the determination of the optimal placement orientation-or combination of orientations-for each SKU, with the objective of storing the total quantity demanded while minimizing dead volume within the allocated slot. As a result, the productivity of the Warehouse Management System (WMS) increased by 14.9%. Additionally, the number of transfer orders completed by a picker per hour rose from 94 to 108 [16].

2.4. ABC Analysis

Inventory classification is a key component of inventory management in many manufacturing companies [17]. In a case study conducted in the retail sector, one of the main challenges identified was the lack of safety stock reference data when calculating the reorder point. This absence of information led to ordering errors, resulting in excess inventory. By correctly applying ABC analysis, the average difference between sales and purchases increased from 7.53% in 2017 to 15.07% in 2018, reflecting a reduction in inventory costs following the implementation of inventory control measures [18]. Similarly, an SME in the hardware sector implemented ABC classification for 200 products, increasing inventory turnover from 3.1% to 8.5%, in conjunction with other complementary tools. In another case study from the automotive industry, two variants of the multi-criteria ABC analysis methodology were evaluated, comparing implementation models based on the primary method and the recursive method applied to two separate warehouses [19]. Additionally, in a textile manufacturing company, ABC classification was employed to reduce internal operation times and optimize warehouse space. The analysis revealed that inactive items occupied a significant portion of the storage area-equivalent to 1,342 pallets-which were subsequently placed on the elimination list [20]. Furthermore, another study emphasized the importance of training warehouse personnel on changes in product locations, ensuring that staff were familiar with product families to enable faster and more accurate retrieval. As a result, order preparation times were significantly reduced, and an estimated annual savings of $11,000 in reverse logistics was achieved by strategically placing visually similar SKUs far apart [21].

2.5. Machine Learning

Sales forecasting is a fundamental tool for operational, tactical, and strategic planning in any organization [24]. Forecasting can be applied in various ways across a company's functions. For instance, a study conducted on a U.S.-based pharmaceutical manufacturer employed both time series methods and machine learning techniques to generate multi-step weekly forecasts. The findings demonstrated that direct sales data can be effectively leveraged to improve forecast accuracy at the manufacturer level [23].

In a similar vein, another study proposed a hybrid model that integrated wavelet transform, Triple Exponential Smoothing (TES), and the Weighted Nearest Neighbor (WNN) algorithm for short-term load forecasting in the California and Spanish electricity markets. The approach yielded highly accurate results, with mean absolute percentage error (MAPE) values below 1 during both regions' spring and summer seasons, reflecting the model's strong performance under those conditions [24]. Likewise, in the automotive sector, a case study proposed a triple exponential smoothing model to forecast the supply of scrap tires from 2019 to 2023. The model demonstrated strong predictive capabilities, with error rates of 3.1% and 3.9% for the years 2019 and 2023, respectively. The consistency between simulated historical data and actual results highlighted the model's robustness and its potential utility in supporting scrap tire recycling initiatives [25]. In another case study, Artificial Neural Networks (ANNs) were applied to optimize variables such as current demand, projected demand for the next three months, current inventory levels, purchasing costs, and transportation expenses. The implementation of ANNs led to an optimized average supply chain network performance of approximately 72%. Moreover, forecast accuracy ranged between 75% and 80%, representing a 2% to 3% improvement over the baseline accuracy, thereby enhancing overall supply chain efficiency [26]. Finally, a study conducted in the food industry applied lean methodologies combined with machine learning tools to address the challenges of product spoilage and inefficient inventory management. As a result, the percentage of spoiled products was reduced by 65.57%.

3. Innovative Proposal

This study adopts a quantitative, pre-experimental design with a single-group approach, comparing pre- and post-intervention data to evaluate the impact of an integrated inventory management model-combining Economic Order Quantity (EOQ), 5S Methodology, Slotting, ABC Analysis, and Machine Learning-on operational performance in a Peruvian automotive accessories SME.

3.1. Fundamentals

The proposed model was developed based on case studies from companies within the same or similar sectors as the spare parts industry, all of which exhibited comparable root causes of inventory management issues in their warehouses. This was achieved through a comprehensive review and analysis of scholarly articles, which enabled the identification of various methodologies and tools.

Among these, Lean Manufacturing emerged as the most widely adopted methodology for warehouse management, particularly through the application of the 5S tool. While its primary objective is to reduce delivery lead time, it also contributes to increased productivity, enhanced quality, improved compliance with customer requirements, higher on-time delivery rates, greater customer satisfaction, and the reduction of waste and machinery inefficiencies [9].

In terms of inventory management, the multi-criteria ABC analysis was identified as an effective approach for optimizing resource utilization and mitigating stockout situations [27]. In relation to demand forecasting, the integration of machine learning has proven valuable in addressing sudden shifts in customer demand. In this regard, the application of artificial intelligence-particularly machine learning-can significantly enhance the performance of supply chain networks. One strategic approach involves embedding machine learning algorithms into Enterprise Resource Planning (ERP) systems [26]. Moreover, a review article published in MDPI emphasized that ARIMA models remain a fundamental technique in time series forecasting, especially in scenarios where data exhibit linear and seasonal behaviors [28]. Similarly, the Economic Order Quantity (EOQ) method was identified as a classical inventory management approach, commonly used to determine optimal order quantities and reorder timing [29]. Lastly, the slotting technique was recognized for its focus on the strategic allocation of products to storage locations within a distribution center, contributing to improved warehouse organization and efficiency [20]. These tools were selected to analyze the company's current situation and formulate a tailored improvement strategy. Using the comparative matrix presented in Appendix 1, it was possible to determine which tools from the state-of-the-art literature aligned with the case study's objectives. As a result, a comprehensive proposal was developed by integrating these tools, aiming to enhance inventory turnover, resolve customer order fulfillment issues, and optimize product distribution within the warehouse, among other improvements. In summary, existing literature provides valuable insights into individual tools such as ABC analysis [18], EOQ models [7], 5S implementations [12], slotting [16], and various machine-learning techniques for forecasting [26]. However, few studies simultaneously integrate these methodologies, particularly in the context of Latin American SMEs dealing with automotive accessories.

Moreover, the majority of case studies originate from European and Asian countries, with limited representation of Peruvian or regional contexts. This research seeks to fill this gap by developing an integrated model that combines multi-criteria ABC classification, ARIMA-based demand forecasting, EOQ calculations, slotting, and the 5S methodology, thereby advancing the state of the art in inventory management for resource-constrained SMEs.

3.2. Construction of the Proposed Model

Based on the analysis of specialized literature and comparable case studies, a management model was developed with the objective of improving the inventory turnover ratio, as depicted in Figure 1. The model is structured into three main components: problem diagnosis, tool implementation, and model validation. In the first phase, the root causes limiting logistics performance were identified using analytical tools such as the Pareto chart, the Ishikawa diagram, and the problem tree. These instruments made it possible to focus interventions on the system's most critical areas.

The second phase involved the application of operational tools. It began with the ABC classification to prioritize strategic inventory items, followed by demand forecasting using machine learning techniques. The Economic Order Quantity (EOQ) was calculated based on these forecasts. Subsequently, slotting techniques and the 5S methodology were implemented to enhance warehouse organization and operational efficiency. Finally, the model was validated through a simulation conducted in Arena software, which enabled performance evaluation across various scenarios. In addition, a pilot implementation was carried out to assess the model's effectiveness in a real-world setting, demonstrating significant improvements in inventory turnover.

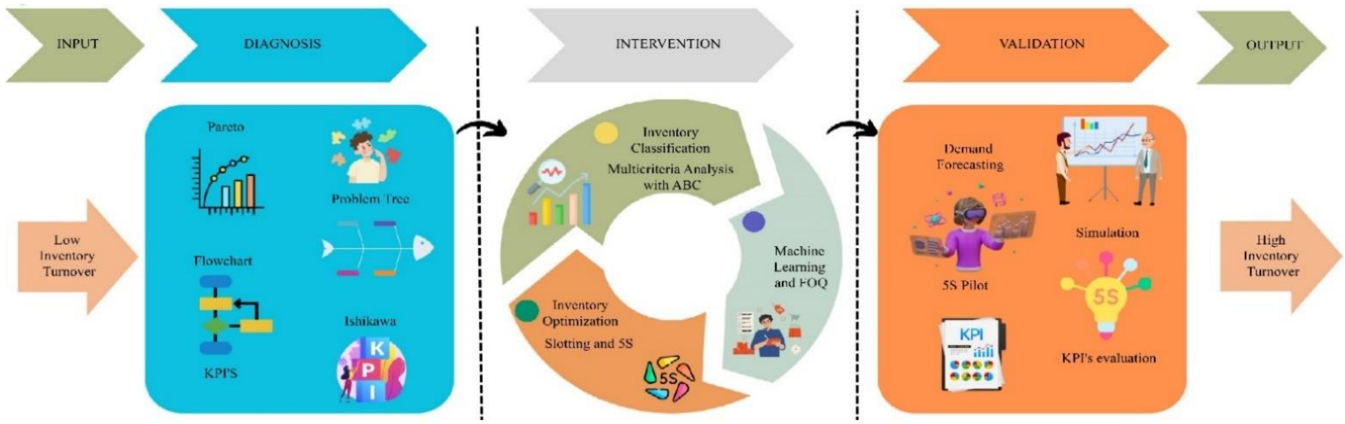


Fig. 1 proposed model

3.3. Component Details

The model is divided into the three components mentioned previously.

3.3.1. Problem Diagnosis

In the initial phase, a comprehensive diagnostic assessment was conducted to identify low inventory turnover as a core issue, using engineering tools to analyze its root causes and operational inefficiencies. The process began with a flowchart outlining the key stages of purchasing, warehousing, and distribution, which revealed significant process bottlenecks. An Ishikawa diagram was subsequently employed to classify the underlying causes into five critical dimensions: methods (inadequate planning), inputs (oversupply), technology (outdated systems), and environment (demand variability). To prioritize corrective actions, the analysis was supplemented by a Pareto chart, which confirmed that 20% of the causes, such as misalignment between purchasing and actual demand, and lack of interdepartmental coordination, accounted for 80% of the adverse effects. In addition, Value Stream Mapping (VSM) revealed redundant activities in stock replenishment processes, while the Five Whys technique uncovered systemic issues, including intuition-based forecasting and non-standardized replenishment procedures. The findings informed the development of targeted actions, including implementing data-driven forecasting models, revision cycles aligned with real demand patterns, and staff training in inventory management. This structured approach addressed the identified root causes and established a solid foundation for improving inventory turnover and reducing costs associated with excess or obsolete inventory.

3.3.2. Tools Identification and Implementation

The study started by talking about different ways to make inventory management better. It began with the smart idea of figuring out which products were really making the company money. This process involved putting items into groups based on how much they added to overall revenue, using the rule that about 20% of products make up about 80% of sales. The result was surprising: only about 20% of the inventory made up most of the sales. This made it possible to focus resources and attention on the most important things instead of spreading them too thin. A demand forecasting model based on AutoRegressive Integrated Moving Average (ARIMA) was developed to improve current practices. The model took into account a number of things, such as past demand, seasonal patterns, and other things that could affect demand. This made the predictions more accurate and cut down on mistakes a lot compared to older methods. The Economic Order Quantity (EOQ) model was used to figure out reorder points and order amounts. It took into account storage costs, ordering costs, and product turnover rates. This method helped us decide when to order more and how much to order. A system was also put in place that could change with changes in demand. This meant that order sizes could be changed based on expected demand levels and past sales data. The layout of the warehouse was also changed to make things run more smoothly. The reorganization was based on how often products were used and how many orders were placed. This cut down on picking times and made the whole process more efficient. A new system was also put in place to keep the warehouse clean and organized. This included getting rid of things that were not needed, setting up specific storage areas, standardizing procedures, and encouraging regular maintenance. Because of this, the accuracy of the inventory went up, the number of mistakes went down, and the time it took to fill orders went down. The combination of these methods worked very well, finding a balance between keeping enough stock on hand, lowering inventory costs, and making operations more efficient. This combination of methods was a big help for small and medium-sized businesses, which often had limited resources. It lets them run their businesses more efficiently without going overboard.

3.3.3. Validation

The company's inventory management processes were replicated in a simulation model built using Arena to see how well the new tools would work. Real data from everyday operations was gathered. Things like how long it took to restock, how often orders came in, and what was happening in the warehouse.

This information was then used to create models that accounted for the unpredictability of these factors. Once the simulation accurately mirrored the state of things, the proposed changes were added, such as putting the 5S methodology into practice and reorganizing the warehouse through a process called slotting. In a corner of the warehouse, a trial run of the 5S system was set up.

The idea was to break it down into steps. Get rid of what is unnecessary, organize what is left, clean up, ensure everything has its place, and keep it that way. By testing it out in a setting, we got some solid numbers to work with, which helped make our simulation more accurate. At the time, we built a model using Arena that took into account things like forecasting sales patterns and figuring out the best order quantities to keep inventory and workflows running smoothly, even when demand changed. By combining simulation and hands-on experimentation, we got a clear picture of how well our theoretical ideas matched up with real-world results.

The arena simulation let us test setups without any risk, and the 5S pilot gave us some valuable lessons about whether our ideas would actually work and how well they would scale up. This approach ensured that our solutions were solid from both a practical standpoint and made sense for the company's day operations.

3.4. Proposed Process

The process for implementing the proposed model is shown in Figure 2. The model is divided into three sequential components: diagnosis, intervention, and validation. Each phase includes a feedback mechanism to ensure that specific criteria are met before advancing.

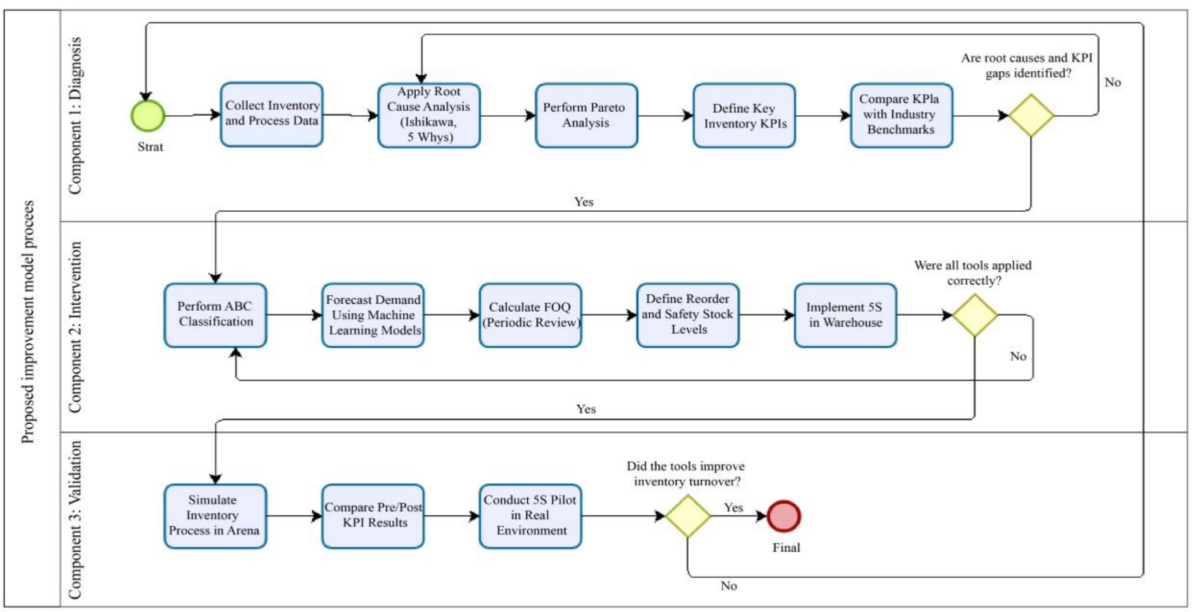


Fig. 2 Implementation of the proposed model process

The implementation begins with the collection of data related to inventory and internal processes. Root cause analysis is then conducted using tools such as the Ishikawa diagram and the 5 Whys technique. Based on the findings, a Pareto analysis is performed to prioritize the most critical causes. Key Performance Indicators (KPIs) for inventory management are then defined and benchmarked against industry standards. If no significant gaps or causes are identified, the process loops back for further analysis.Once improvement opportunities are confirmed, the intervention phase is initiated. The inventory is first categorized using the ABC classification method. Subsequently, demand is forecasted using machine learning models, specifically ARIMA. The economic order quantity (EOQ) is then calculated under a periodic review policy, followed by the definition of reorder points and safety stock levels. To enhance operational efficiency, the 5S methodology is implemented in the warehouse. If any tools were incorrectly applied, adjustments are made before proceeding. During the validation phase, the inventory process is simulated using Arena software. The simulation is driven by the output of the ARIMA forecast and the EOQ analysis. This allows for testing various scenarios and evaluating the impact of the proposed improvements. Pre- and post-intervention KPIs are compared, and a pilot test of the 5S methodology is conducted in a selected warehouse area. If the applied tools lead to improved inventory turnover, the model is validated. Otherwise, the process is re-evaluated starting from the earlier phases.

3.5. Indicators

To assess the performance and impact of the proposed model, specific indicators were defined in alignment with each of its components. Inventory turnover. This indicator is commonly used to evaluate products that generate a significant portion of the company's revenue or require substantial investment due to their high acquisition cost [22].

$$Inventory\ turnover = \frac{Sales\ Cost}{Average\ inventory} \quad (1)$$

Movement Time. This indicator refers to the time dedicated to transfers during the product-picking process. The implementation of 5S and Slotting methodologies has been shown to reduce this time by up to 50%, thereby improving operational efficiency in the warehouse.

$$Movement\ time = \sum Transfer\ activities\ time \quad (2)$$

On Time In Full (OTIF). Based on the case studies reviewed, this indicator must improve by 33.29% to reach the target value, demonstrating effective customer service and high customer satisfaction [30].

$$OTIF\ (\%) = On\ Time\ x\ In\ Full \quad (3)$$

Location Registration Accuracy (LRA). This indicator evaluates the consistency between the physical location of products and the information recorded in the inventory system. Applying the Multi-Criteria ABC analysis can increase this indicator by approximately 15% by improving the organization and traceability of stock within the warehouse.

$$ERU(\%) = \frac{Correct\ Locations}{Total\ of\ Locations} \quad (4)$$

Average Picking Time. This indicator provides insights into opportunities to enhance operational efficiency, reduce logistics costs, and improve service levels. According to a referenced study, the implementation of methodologies such as 5S and ABC analysis led to a 20.34% reduction in picking time by improving the organization and accessibility of products within the warehouse [31].

$$Average\ picking\ time = \frac{Total\ picking\ time}{Number\ of\ orders} \quad (5)$$

Inventory Record Accuracy (IRA). Measures the accuracy of physical inventory relative to inventory in the system. The Kardex tool can increase the ERI by 28.47%.

$$ERI(\%) = \frac{Correct\ counts}{Total\ counts} \quad (6)$$

Total logistics cost. This indicator makes it possible to measure and control the set of costs associated with logistics operations, including storage, transportation, ordering, and inventory management. In a referenced study, it was applied considering warehouse space limitations to define maximum and minimum inventory levels to be maintained at the buyer's plant warehouse, as well as the optimal delivery quantity from the supplier to each buyer, to minimize total supply chain costs [36].

$$TLC = C_{storage} + C_{inventory} + C_{ordering} + C_{transportation} + C_{material\ handling} \quad (7)$$

4. Validation

4.1. Description of the Scenario

This research was conducted at a company dedicated to retailing automotive accessories, with its main warehouse in the La Victoria district of Lima Province, Peru. The proposed model and associated tools were implemented in two distinct stages aimed at improving inventory turnover.The first stage involved a four-week pilot implementation to assess the feasibility and effectiveness of the proposed improvements in a real operational environment. The second stage consisted of a simulation that modeled the end-to-end inventory process, from the reception of spare parts to the picking and packing activities triggered by purchase orders.

4.2. Initial Diagnosis

The company's primary issue was identified as low inventory turnover, which averaged 3.49 cycles per year over the past five years. This performance reflected inventory excesses equivalent to 13.95% of the average cost of sales between 2018 and 2022. Process analysis revealed that 28% of the inefficiencies were attributable to inaccurate demand planning, largely due to the absence of a structured forecasting system. Additionally, 26% resulted from poor inventory management practices, including the lack of product classification and excessive travel time during picking operations. Based on this diagnosis, a problem tree was developed, as illustrated in Figure 3.

4.3. Validation Design

In the first phase, data collection was carried out through interviews with company representatives, gathering information related to best-selling products, inventory volumes, and available storage capacity. During this stage, the benefits of the proposed model for driving organizational improvements were also presented and discussed with stakeholders.

Based on the collected data, the second phase involved prioritizing product families using the ABC multi-criteria analysis supported by a Pareto chart. This classification was based on the historical demand for components over the past five years. As shown in Table 1, Category A, which includes the most critical items, represented 10% of the total product families-comprising 19 families-and accounted for 79% of the total inventory value. Category B included 20 families (11%)and represented 16% of the total investment. Lastly, Category C contained theargest number of product families; however, it contributed only 5% of the total inventory value. Additionally, five product families were selected from the 19 included in Category A: light bulbs, spark plugs, relays, silicone, and caps. These five families account for approximately 47% of the total inventory value.

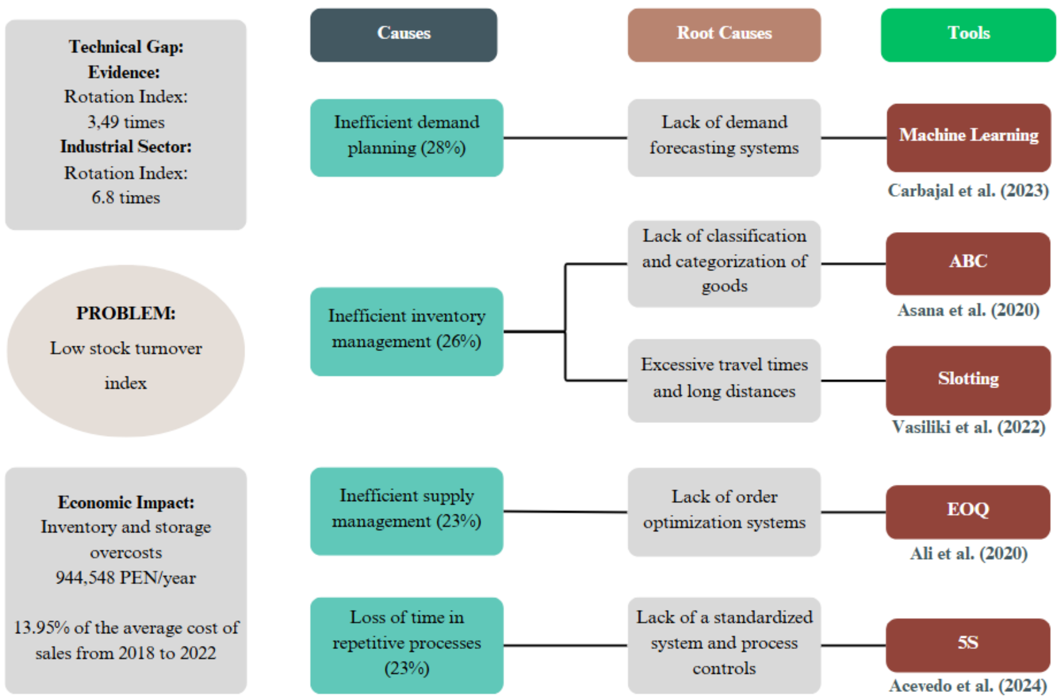


Fig. 3 Problem tree

Table 1. ABC classification by family

Categoría	Rango	Cantidad	%Artículos	%Artículos acumulados	% Inversión	%Inversión acumuladas
A	[0-80%]	19	10%	10%	79%	79%
B	[80-95%]	20	11%	21%	16%	95%
C	[95%-100%]	147	79%	100%	5%	100%
Total		186	100%		100%	

Table 2. Percentage of inventory value per family

Familia	Inversión (Soles)	Participación Relativa Inventario
Foco	1,481,048.68	20.32%
Bujía	733,418.33	10.06%
Relay	535,028.56	7.34%
Silicona	385,207.12	5.29%
Tapa	301,054.75	4.13%
TOTAL	**3,435,757.44**	**47.14%**

Given their substantial share of the overall investment, they were chosen as units of analysis for the application of improvement tools. This selection enables a more efficient and targeted approach, focusing efforts on the areas with the highest potential impact on inventory turnover and operational performance, as detailed in Table 2. Based on the results of the previous phase, the third stage was carried out, which focused on demand forecasting using machine learning techniques. The Python programming language was employed through the Spyder environment to evaluate the performance of various forecasting models, using metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD).

The models tested included Random Forest, Support Vector Machines (SVM), ARIMA, SARIMA, Holt-Winters, and Naive Bayes. The evaluation of these models across the five selected product families revealed that ARIMA consistently achieved the lowest MAPE in three of them: spotlight (9.02%), spark plug (14.00%), and relay (13.49%). Table 3 presents a comparative summary of the percentage errors associated with each forecasting method.

Table 3. MAPE regarding the evaluation of forecasting models

Model	Spotlight Consumption Forecast MAPE	Spark plug Consumption Forecast MAPE	Relay Consumption Forecast MAPE	Silicone Consumption Forecast MAPE	3id Consumption Forecast MAPE
Naive Bayes	13.98%	16.43%	15.48%	24.44%	22.37%
ARIMA	9.02%	14%	13.49%	19.36%	14.95%
SARIMA	15.11%	18.99%	19.26%	40.02%	25.65%
Holt-Winters	16.27%	15.45%	18.67%	34.10%	23.12%
Random Forest	9.74%	28.15%	19.97%	19.19%	40.58%
SVM	15.90%	15.44%	12.69%	47.55%	18.60%

From this, univariate distribution plots were created to evaluate demand behavior. Violin plots were used for each family, as shown in Figure 4. These plots reflect greater volume and stability in the demand forecast values for the target product. Furthermore, the average and median are very close for almost all products, indicating a fairly balanced distribution without extreme bias. The following plots (Figures 5, 6, 7, 8, and 9) present the forecast results for each product family, based on the training and test datasets. Each plot includes the corresponding performance indicators pr eviously discussed, providing a visual representation of the model's predictive accuracy. Figure 5 shows the results for the lid family, Figure 6 for silicone, Figure 7 for relay, Figure 8 for spark plug, and Figure 9 for spotlight. This breakdown allows for a comparative analysis of the model's predictive performance across the different product categories.

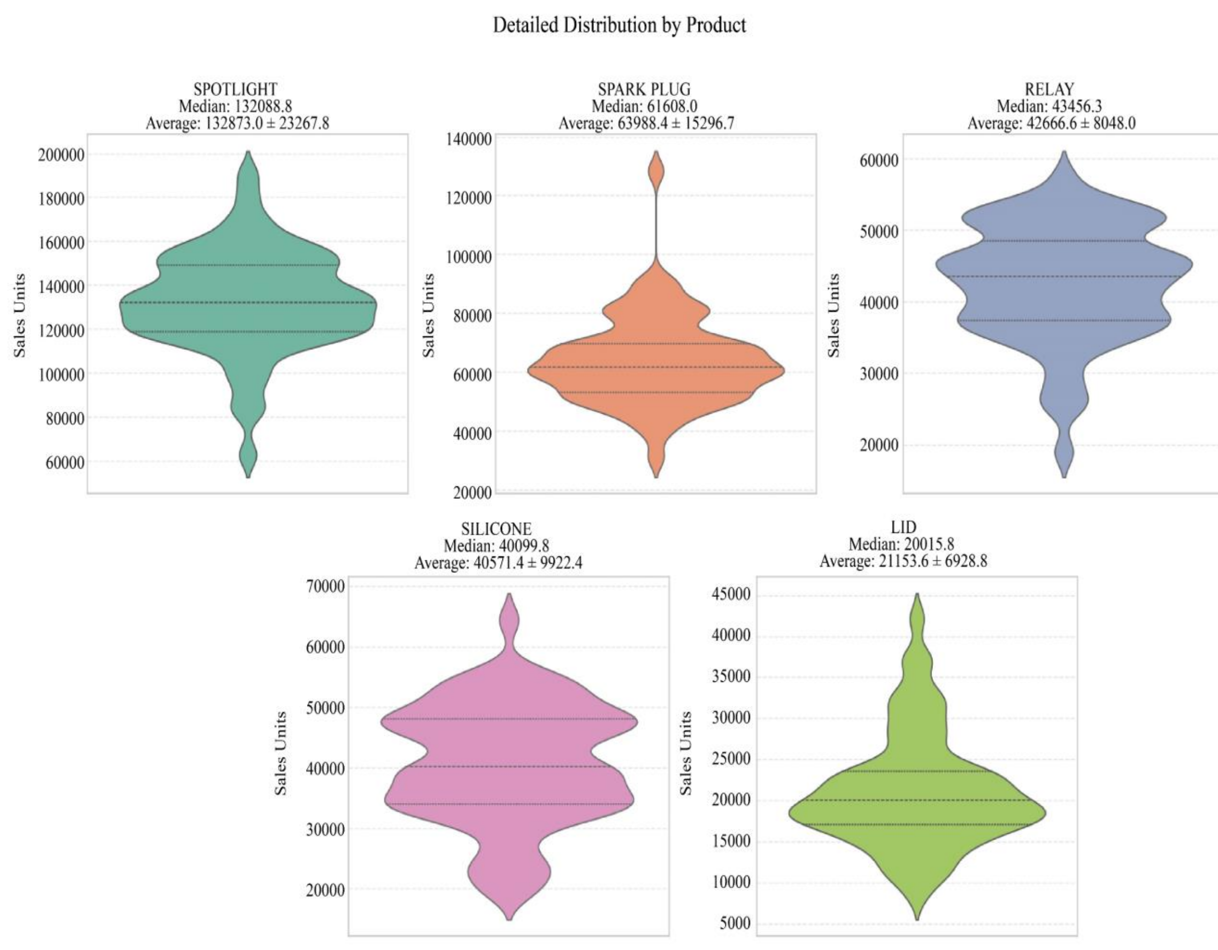


Fig. 4 Detailed distribution by product

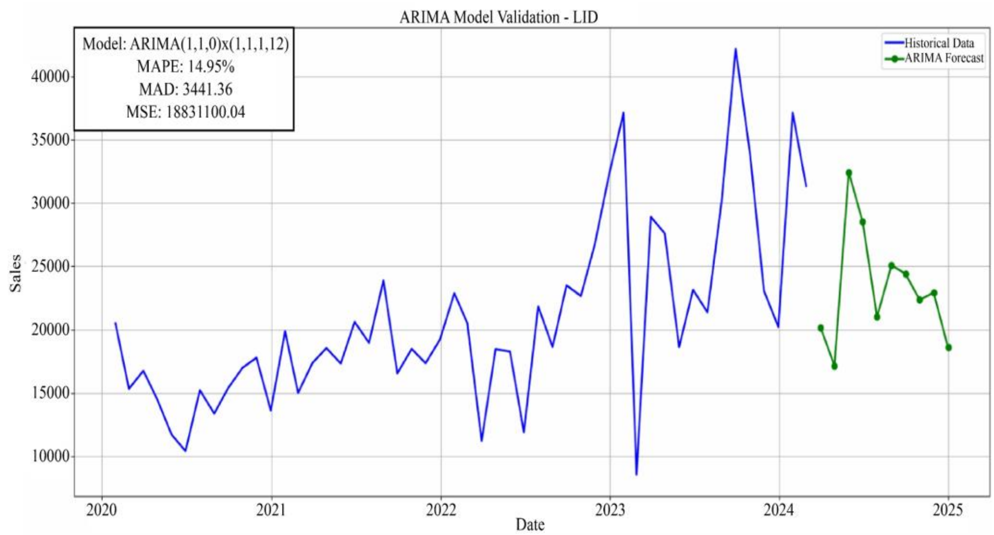


Fig. 5 Model validatión – Lid

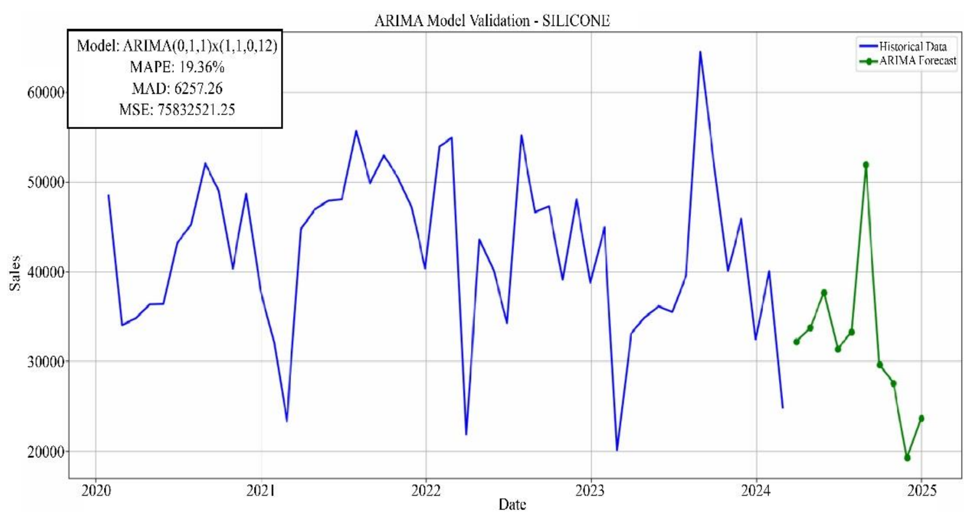


Fig. 6 Model validatión – silicone

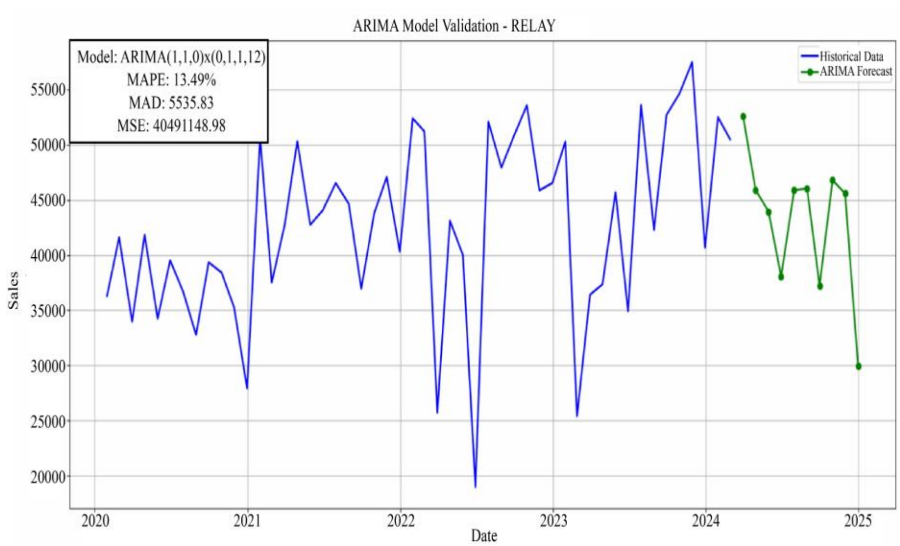


Fig. 7 Model validation – relay

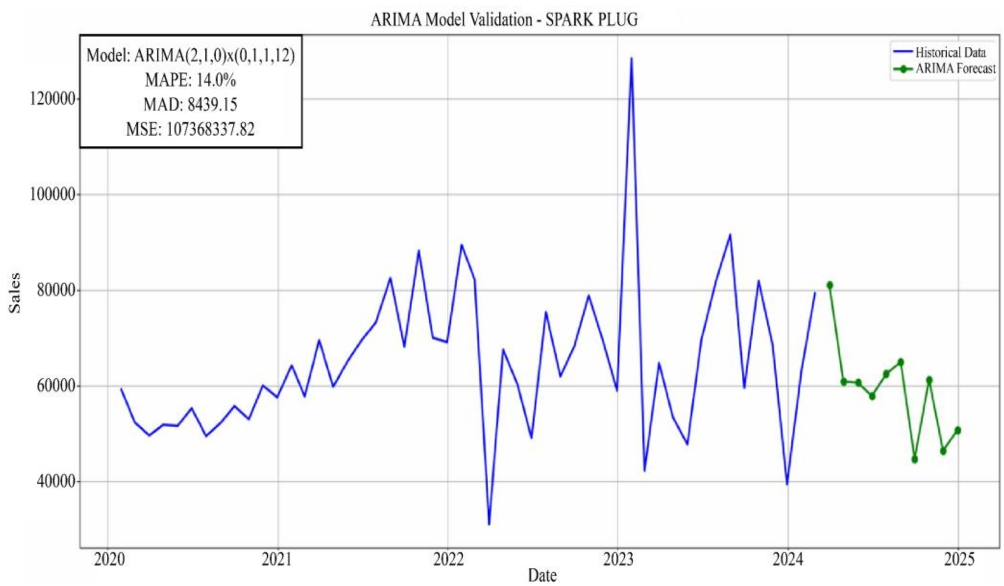


Fig. 8 Model validatión - spark plug

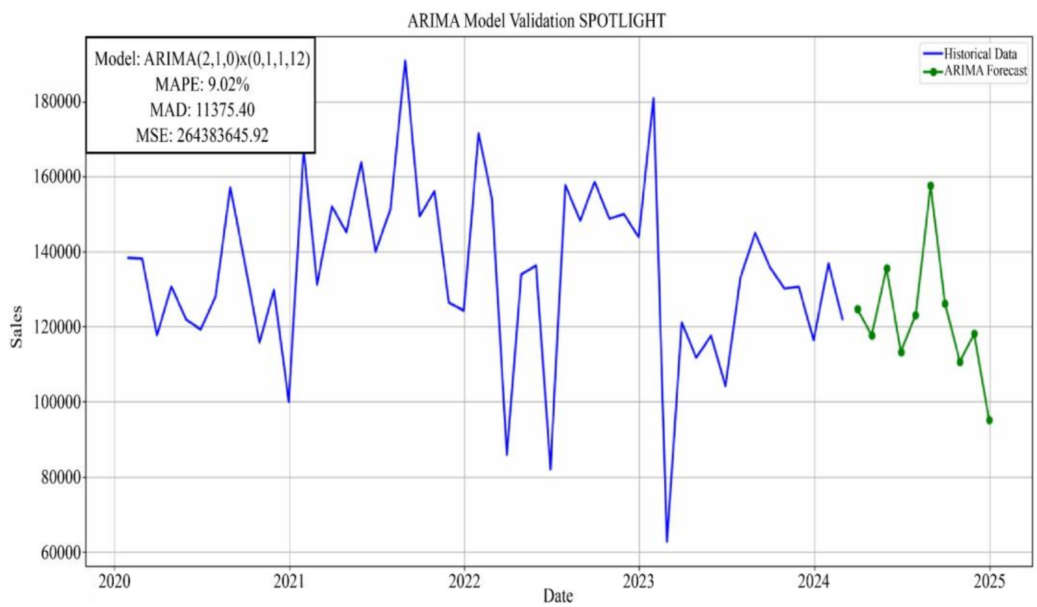


Fig. 9 Model validatión - spotlight

In the fourth phase, following the demand forecasting conducted using machine learning techniques for the five selected product families, the five most representative items from each family were selected for further analysis. These items had been previously classified through ABC analysis and based on their respective market share percentages. Using these values, demand estimates were extrapolated to the company's entire product portfolio. Subsequently, the Economic Order Quantity (EOQ) method was applied under a periodic review policy. This approach enabled the determination of both the optimal order quantity and the appropriate replenishment frequency for each item analyzed. Table 4 presents the calculation of the cost per order, which was obtained by dividing the total annual expenditure on orders by the number of orders placed during 2024.This figure also considers the buyer's time distribution, with 70% of the workday allocated to order management and 30% to market research. Based on this estimation, the approximate cost per order was 68.02 PEN. Table 5 presents the annual storage cost, estimated as 18% of the average inventory value for the year 2022. This percentage reflects the expenses related to maintaining stock, including warehousing, insurance, depreciation, and obsolescence.It serves as a critical input in the Economic Order Quantity (EOQ) model, influencing the calculation of optimal inventory levels and replenishment strategies.

Table 4. Cost of placing an order

Variable	Value
Salario mensual del encargado de compras (PEN)	4 000
Número de meses al año	12
Salario anual (PEN)	48 000
% Tiempo dedicado a realizar pedidos	70%
Costos de realizar pedidos al año (PEN)	33 600
Número de pedidos al año	494
S: Costo de realizar un pedido (PEN)	**68,02**

Table 5. Annual storage cost

Variable	Value
Annual Storage Cost (PEN)	387 696
Average Inventory Value (PEN)	2 154 063
I: % Annual Storage Cost	**18%**

Based on the previously estimated demand and cost data, the Economic Order Quantity (EOQ) was calculated using the classical model.

This calculation allowed for the determination of the optimal order quantity that minimizes the total cost associated with ordering and holding inventory.

$$EOQ = \sqrt{(2DS / H)} \tag{8}$$

In the equation shown, D denotes the annual demand for the product, S refers to the cost per order, and H corresponds to the annual holding cost per unit. The following formula was also applied to calculate the Safety Stock (SS) level.

$$SS = Z \times \sigma \times \sqrt{L} \tag{9}$$

In the equation, Z denotes the value corresponding to the desired service level, σ represents the standard deviation of demand, and L refers to the replenishment lead time expressed in days. Finally, the Reorder Point (ROP) is calculated using the following formula.

$$ROP = D \times L + SS \tag{10}$$

These tools enable optimized inventory management by balancing ordering and storage costs. Once the equations for calculating the Economic Order Quantity (EOQ) and safety stock were applied, the results were validated through a simulation developed in Arena software, initiating the fifth phase of the model. This simulation allowed for the verification of the accuracy of the calculations and the evaluation of system performance under different scenarios, ensuring optimal and efficient inventory decisions. An 8-hour workday and a simulation period of 360 days were considered, with 50 replications conducted to meet the required error margin. The simulation was applied to both the current process and the improved scenario. Figure 10 presents the complete simulation model for the improved scenario, encompassing the entire workflow from component receipt to the picking and packing stages, which supports a comprehensive evaluation of inventory management processes.As illustrated in Figure 11, the AS IS model reveals that, in the absence of an optimized purchasing strategy, orders tend to be large and infrequent, leading to excess inventory and low product turnover. In contrast, the model to be modeled, depicted in Figure 12, shows significant improvements: smaller and more frequent orders reduce inventory days, optimize storage costs, and enhance turnover rates, thereby increasing overall system efficiency. For the pilot test, the 5S methodology was implemented to organize the warehouse and eliminate non-value-adding elements. Initially, all available tools were recorded using a Kardex system, which facilitated the registration of incoming and outgoing items. This process is depicted in Figure 13. As a result of using the Kardex, an Equipment Retrieval Index (ERI) of 95.67% was achieved-an improvement of 47.48% compared to the initial baseline.

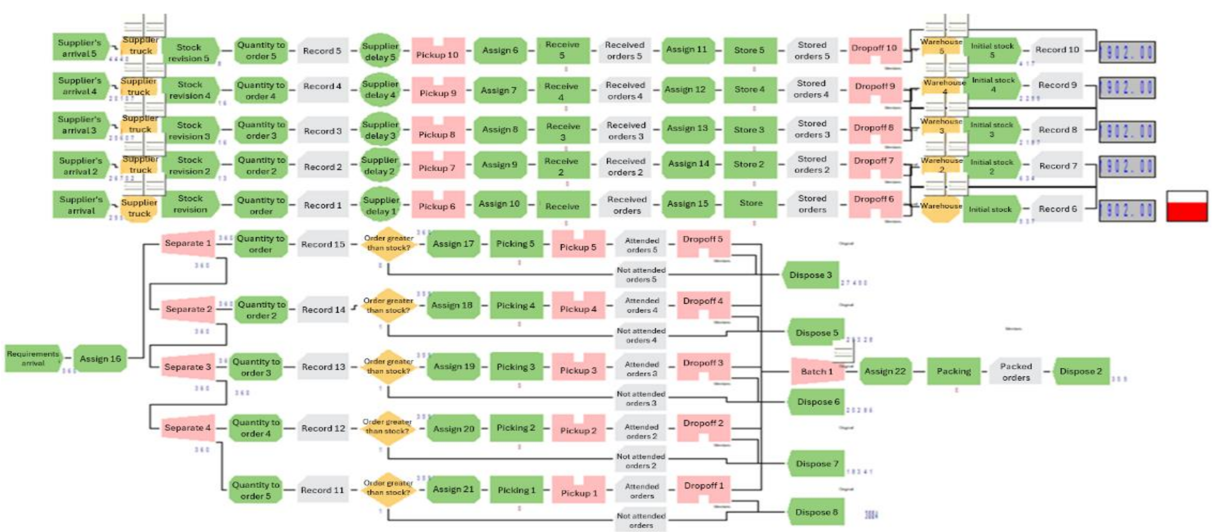


Fig. 10 Simulation model

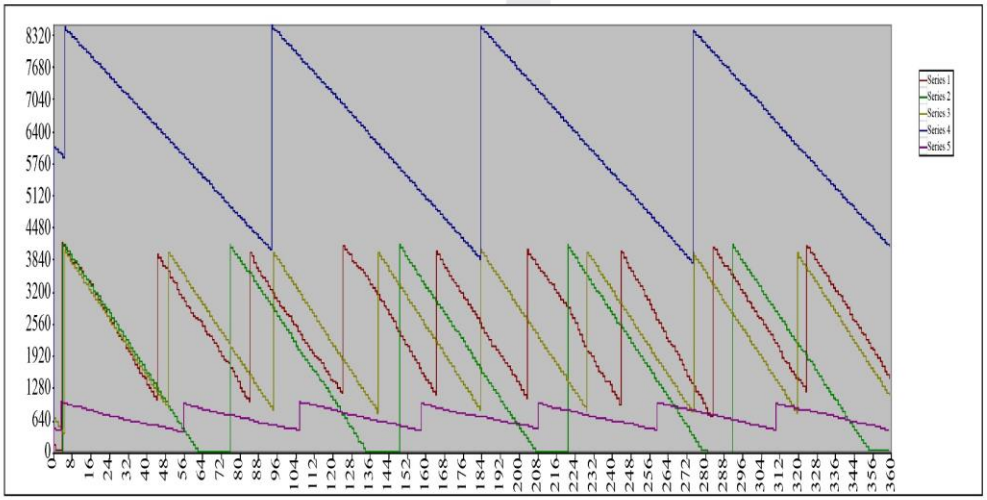


Fig. 11 Inventory turnover behavior in the AS IS model

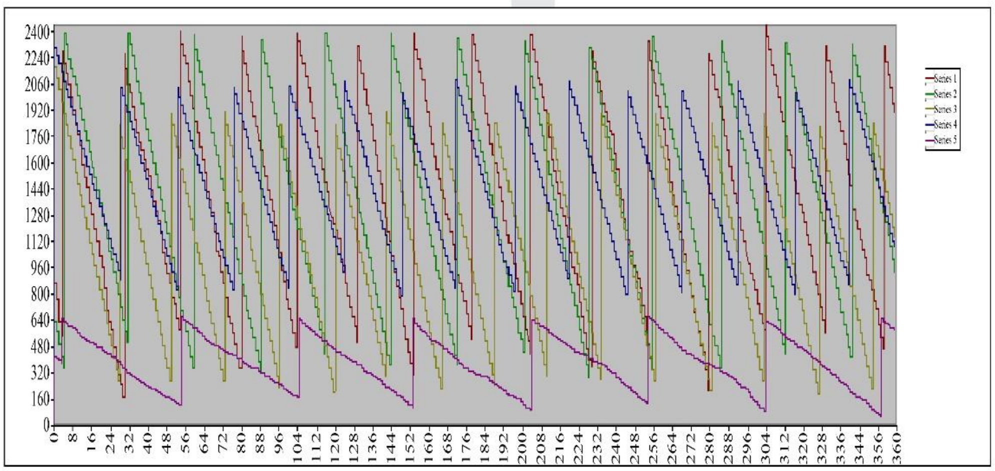


Fig. 12 Inventory turnover behavior in the to be model

Kardex (income and expenditure)										
Date	Family	Product	Entry Qty	Entry Unit Cost (PEN)	Entry Total Cost (PEN)	Exit Qty	Exit Unit Cost (PEN)	Exit Total Cost (PEN)	Balance Qty	Balance Total Cost (PEN)
1/07/2024	Spotlight	Spotlight h4 12v 60/55w p43t narva	5,000	PEN 5.37	PEN 26,850.00				5,000	PEN 26,850.00
5/07/2024	Spotlight	Spotlight h4 12v 60/55w p43t narva				1,200	PEN 5.37	PEN 6,444.00	3,800	PEN 20,406.00
2/07/2024	Spark plug	Spark plug (7938) (fr8dc) 5/8 hyundai	4,000	PEN 4.75	PEN 19,000.00				4,000	PEN 19,000.00
10/07/2024	Spark plug	Spark plug (7938) (fr8dc) 5/8 hyundai				1,500	PEN 4.75	PEN 7,125.00	2,500	PEN 11,875.00
3/07/2024	Relay	Relay 12v 5p bosch	3,000	PEN 7.25	PEN 21,750.00				3,000	PEN 21,750.00
15/07/2024	Relay	Relay 12v 5p bosch				1,000	PEN 7.25	PEN 7,250.00	2,000	PEN 14,500.00
4/07/2024	Silicone	Silicone blister 85gr versachem	2,500	PEN 9.10	PEN 22,750.00				2,500	PEN 22,750.00
12/07/2024	Silicone	Silicone blister 85gr versachem				800	PEN 9.10	PEN 7,280.00	1,700	PEN 15,470.00
6/07/2024	Lid	Radiator lid 9lbs chica few	1,000	PEN 9.61	PEN 9,610.00				1,000	PEN 9,610.00
16/07/2024	Lid	Radiator lid 9lbs chica few				300	PEN 9.61	PEN 2,883.00	700	PEN 6,727.00

Fig. 13 Kardex used in the pilot test

Additionally, deficiencies were identified in the availability of Personal Protective Equipment (PPE) and the lack of a designated storage area within the warehouse. To address this, and in alignment with Seiketsu (Standardize) and Seiso (Clean) principles, a dedicated shelf was installed to organize the PPE more effectively, facilitating access and management by warehouse personnel. Before implementation, workers were informed about the importance of maintaining a specific area for PPE to promote safety and support efficient operations. This improvement is illustrated in Figure 14. As part of the warehouse improvement initiatives, changes were made to address safety and organization issues related to the storage of Personal Protective Equipment (PPE).

Initially, there was no designated area for PPE, and boxes obstructed the passageways, posing a safety hazard. After implementing the improvements, a dedicated shelf was installed to store PPE, including safety helmets.

These changes are illustrated in Figure 15, which shows the conditions before and after the intervention. Additionally, as part of the tool's implementation, a bin was incorporated to separate unnecessary materials, such as corrugated cardboard, which is commonly used for transporting spare parts within the warehouse, as shown in Figure 16.

Fig. 14 Interview with operators

BEFORE	AFTER
	
Description	**Description**
There are no PPE and they do not have a predetermined location. In addition, the passageway is full of boxes and objects that obstruct the passageway.	A rack was added to keep the safety helmets in a visible place for the workers. This would significantly improve the order in the warehouse.

Fig. 15 Inclusion of a shelf for PPE storage

Fig. 16 Waste segregation bins inclusion

Furthermore, floor markings and directional arrows were added to delineate the passageways and storage areas. This aligns with the Seiri principle, which focuses on distinguishing essential items from non-essential ones, thereby improving organization and visual control. Figure 17 presents the before-and-after results of this improvement.

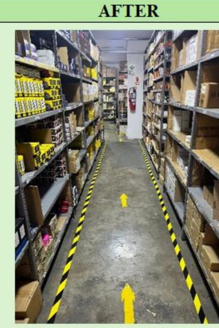
BEFORE	AFTER
	
Description	**Description**
There were no boundaries between the shelves and the passageway, nor were there signs for the passage of workers through it.	Boundary tapes were included, as well as signaling arrows in the passageway.

Fig. 17 Boundary tapes and signaling arrows inclusion

To ensure the effective implementation of the tool over time, we established inventory management procedures. These procedures include conducting a comprehensive physical inventory at the end of each fiscal year to verify stock levels and reconcile them with inventory records. This process helps determine the actual year-end inventory value. Additionally, an audit was conducted to assess the tool's performance in the warehouse. There was a recorded improvement of 35.95% between the initial and final audits. Figure 18 illustrates a summary of these results.

The slotting tool was finally implemented to optimize the warehouse layout according to product characteristics and movement patterns. This change led to a substantial decrease in the average order picking time, reducing it from 15.32

minutes to 6.13 minutes per order, representing a 60% improvement. Figure 19 shows the warehouse layout before the optimization, while Figure 20 illustrates the layout after the changes were made. In order to achieve a 60% improvement. Figure 19 presents the warehouse layout before the improvement, while Figure 20 illustrates the layout after the optimization.

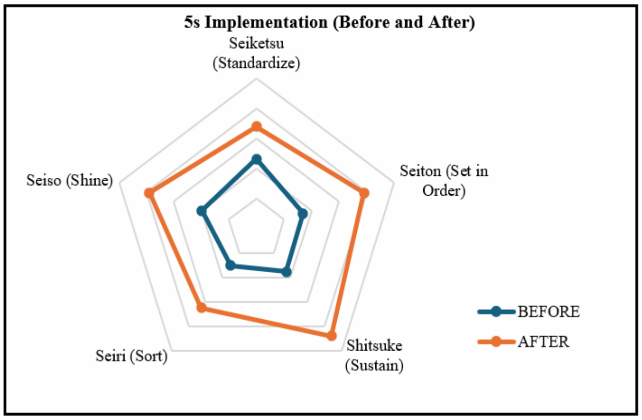


Fig. 18 5S Audit diagram

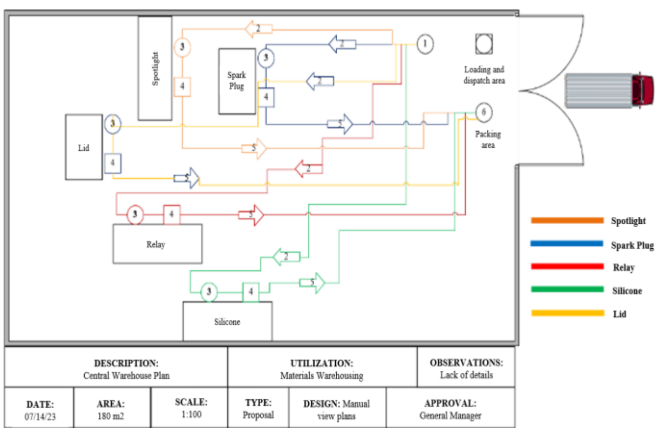


Fig. 19 Warehouse layout before improvement

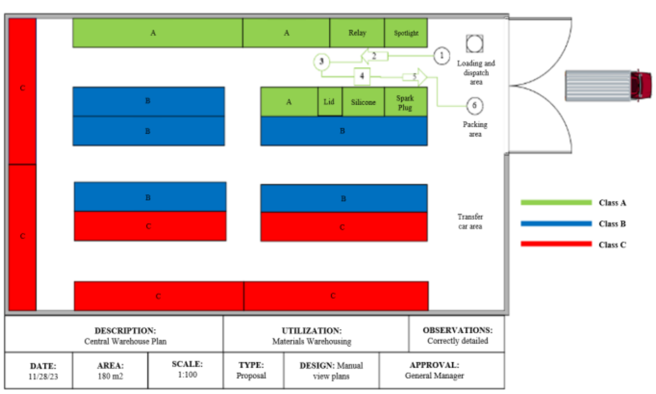


Fig. 20 Warehouse layout after improvement

The application of slotting methodology and ABC analysis led to a strategic relocation of products, optimizing the overall warehouse layout, as shown in Figure 21. This improvement was further supported by the implementation of SKU labeling on shelves, which made operational identification easier. As a result, the Unit Recovery Efficiency (URE) indicator significantly improved, increasing from 75.44% to 92.56%, thereby exceeding the target value of 89.85%. The improvement proposal focused on modifying the inventory policy and determining optimal stock levels to standardize warehouse inventory management. This strategy relies on periodic reviews, inventory verification, and purchases calculated as the difference between the maximum and current stock levels, taking established lead times into account.

BEFORE	AFTER
	
Description	**Description**
There were no numbers to guarantee the location of the products in the warehouse.	Numbers were added for each SKU. This would speed up the process of locating products on the respective shelves.

Fig. 21 SKU numbering on shelves

A significant inventory reduction is expected, which will optimize resource allocation and lower costs associated with inventory management and storage. This strategic measure marks a substantial step toward more efficient inventory control, aligned with the organization's operational needs.As a result of the pilot implementation and simulation, inventory turnover improved by 33.43%, while average inventory levels decreased by 30%, effectively addressing the issue of excess stock.

Additionally, the On Time In Full (OTIF) indicator rose from 62.14% to 82.26%, demonstrating a stronger commitment to fulfilling customer orders within the agreed timeframe. The percentage of removal of unnecessary items also increased significantly, from 60.23% to 84.67%. Moreover, picking time and total logistics costs were reduced by 60% and 19.95%, respectively.

Finally, the Inventory Record Accuracy (IRA) and Location Record Accuracy (LRA) indicators improved significantly, reflecting better data integrity and enhanced warehouse management. These results are summarized in Table 6, providing a comprehensive overview of the improvements achieved through the integrated model.

Table 6. Indicators Results

	Indicator	As Is	To Be	Obtained
General	Inventory turnover	3.5 times	6.7 times	4.67 times
	Average Inventory	2100 units	1806 units	1470 units
	OTIF	62.14%	92.00%	82.26%
5S	Percentage of removal of unnecessary elements	60.23%	78.56%	84.67%
Machine Learning	Mean Absolute Percentage Error (MAPE)	56.42%	12.45%	9.02%
Slotting	Picking Time	15.32 min	7.8 min	6.13 min
Kardex	IRA	64.87%	97.50%	95.67%
EOQ	Total Logistics Cost	PEN 556,000.00	PEN 503,180.00	PEN 445,077.58
ABC	LRA	75.44%	89.85%	92.56%

5. Discussion

Based on the results obtained from implementing the improvement proposal, the effectiveness of the selected tools in enhancing key performance indicators-such as inventory turnover and On-Time In-Full (OTIF)-was successfully validated. The outcomes demonstrate significant improvements across various metrics. For example, the 5S methodology exceeded expectations, achieving an increase of 40.58% in the elimination rate of unnecessary items, resulting in a final value of 84.67%.

The implementation of Slotting reduced picking time by nearly 60%, with an average of 6.13 minutes per order. EOQ reduced total logistics costs by 19.95% (PEN 445,077.58 annually), surpassing the target. The ABC multi-criteria tool reached an effectiveness rate of 92.56%, reflecting an 18.5% improvement. The Kardex tool achieved an effectiveness rate index (IRA) of 95.67%, representing a 30.80% increase from the initial value. These results confirm the practical value of the integrated inventory management model developed in this study.Compared to previous studies, which typically implement isolated tools, this research demonstrates the advantages of integrating multiple methodologies within a single, cohesive model.

While some studies focus solely on ABC analysis [17, 18], EOQ [7, 9], 5S application [13], or machine learning forecasting [24, 25], few have explored the combined application of these tools in a unified framework. This research bridges this gap by integrating ABC classification, EOQ, Slotting, 5S, and Machine Learning forecasting, resulting in significantly improved inventory turnover and operational efficiency. This integrative approach represents a notable contribution to the literature, particularly in the context of Peruvian SMEs in the automotive accessories sector, where the application of Machine Learning-based forecasting has not been extensively explored [25]. The study's findings suggest that integrating Lean Manufacturing tools with advanced forecasting techniques, such as Machine Learning, can significantly enhance inventory management in SMEs. This approach improves key performance indicators and contributes to more efficient resource utilization and operational efficiency. The model's adaptability positions it as a replicable solution for similar companies seeking to optimize inventory turnover and warehouse management practices. Moreover, this research supports the implementation of continuous improvement methodologies and technological tools in developing economies, offering a path toward increased competitiveness and sustainability.Despite the promising results, this study was conducted in a single company with a specific focus on automotive accessories in the Peruvian market, which may limit the generalizability of the findings. Additionally, the study was implemented over a short timeframe (six months), which restricts the assessment of long-term impacts and the durability of improvements achieved. Future research could expand the scope by including multiple companies, different industrial sectors, and longer observation periods. Future studies should investigate the long-term effects of integrating Machine Learning and Lean tools in inventory management and explore their applicability across diverse industrial contexts. A larger sample size, including different product categories, and incorporating additional technologies such as ERP systems and predictive analytics, could provide deeper insights and support more robust generalization of results.

5.1. Economic Validation

The economic evaluation of the project was conducted over 12 months. The total estimated investment was PEN 13,054.36. To assess the financial viability of the proposal, several key indicators were analyzed: Net Present Value (NPV), Internal Rate of Return (IRR), Benefit-Cost Ratio (BCR), and Payback Period. As detailed in Table 7, the project generated an NPV of PEN 34,390.66, while the IRR was calculated at 82.95%, significantly surpassing the Opportunity Cost of Capital (OCC), which was set at 22.8%. Furthermore, the BCR was 4.76, indicating that a return of 4.76 soles was achieved for every sol invested. The payback period was 2.52 months, demonstrating a quick recovery of the initial investment.

Table 7. Economic indicators results

Indicator	Value
NPV	PEN 34,391
IRR	82.95%
BCR	4.76
Payback	2.52 months

On the other hand, in environmental terms, the application of Leopold's matrix made it possible to identify the main impacts associated with warehouse operations. One of the most significant findings was the carbon dioxide emission level, which reached 5,516.55 kg during the year 2024, as detailed in Table 8. In response to the impacts identified, alternative solutions were proposed to mitigate the environmental footprint of warehouse operations. Among these, the incorporation of hybrid and electric vehicles for the transportation of automotive spare parts from suppliers' warehouses to the company's warehouse was suggested, aiming to reduce carbon dioxide emissions.

Additionally, noise pollution generated by forklifts, due to both the noise and gas emissions produced during product handling, was recognized as an environmental concern. To address this, a contingency plan was proposed, including training sessions for personnel on the proper use of forklifts and an evaluation for the replacement of obsolete machinery with quieter and more efficient equipment, based on the results of an acoustic study of the warehouse.

Table 8. Leopold matrix of environmental impacts

Activities / Environmental Factors	CO_2 emissions	Acoustic Contamination	Gas Emissions	Fuel Consumption	Air Contamination	Internal noise level	Residues	Total Impact
Traditional transport vehicles utilization	-8	0	-7	-9	-8	0	-2	-34
Use of old forklifts	-5	-7	-6	-5	-4	-7	-1	-35
Electric/hybrid vehicles: Incorporation	7	0	6	8	7	0	1	29
Efficient use of forklifts Training	4	6	4	4	3	6	1	28
Modern equipment replacement	5	8	6	5	4	8	1	37

Moreover, in the analyzed sector, significant opportunities were identified for advancing research on inventory management tools specifically adapted to organizations involved in purchasing and selling automotive spare parts in Latin American countries such as Peru, Chile, and Argentina.

This need stems from the observation that most of the studies reviewed during the systematic literature analysis originated in Western European and Asian countries, particularly India, Pakistan, Indonesia, and Japan. This trend highlights the limited representation of research focused on Latin American contexts, revealing a potential gap in the scientific literature and a strategic opportunity to promote research that addresses this region's unique operational and logistical characteristics.

6. Conclusion

This research addressed the critical problem of low inventory turnover in a small Peruvian commercial company specializing in automotive accessories, significantly below the industry benchmark, resulting in excess stock and high storage costs. The integrated inventory management model proposed in this study, which combines ABC classification, Economic Order Quantity (EOQ), slotting, 5S methodology, and machine learning-based demand forecasting, achieved substantial improvements in key performance indicators, including a 33.43% increase in inventory turnover, a 30% reduction in average inventory, and significant gains in Inventory Record Accuracy (IRA) and Location Record Accuracy (LRA).

These findings suggest that the integration of Lean Manufacturing tools with advanced forecasting techniques can provide an effective solution to inventory management challenges in Peruvian commercial SMEs, offering a replicable and sustainable model for similar contexts in developing countries. Despite these promising results, the study was conducted in a single company over a relatively short implementation period, which may limit the generalizability of the results. Future research should focus on extending the model's application to different commercial sectors, assessing its long-term impact, and integrating additional technologies such as ERP systems and predictive analytics to strengthen supply chain resilience.

Overall, this study demonstrates the potential of combining Lean tools with machine learning to address operational inefficiencies in the automotive accessories retail sector, constituting a significant contribution to scientific knowledge and a solid foundation for future research in Peruvian SMEs and similar contexts.

References

[1] Sierra Bautista, and Fabian Mauricio, "Improvement Plan in the Storage and Dispatch Processes of the Company Electrical Distribution JE SAS," *Universidad Industrial de Santander*, Bucaramanga, Colombia, pp. 17-130, 2017. [Google Scholar] [Publisher Link]

[2] Edward Frazelle, *Supply Chain Strategy: The Logistics of Supply Chain Management*, McGraw-Hill Education, 2002. [Google Scholar] [Publisher Link]

[3] Micro and Small Businesses in Peru Results in 2021, ComexPerú - Peruvian Foreign Trade Society, 2021. [Online]. Available: https://www.comexperu.org.pe/upload/articles/reportes/reporte-comexperu-001.pdf

[4] Juan Carlos Capuñay, APEC Summit Bangkok 2022, El Peruano, 2022. [Online]. Available: https://www.elperuano.pe/noticia/198167-cumbre-apec bangkok-2022

[5] Editorial Management, 66% of Companies in the Country have an Incipient Level of Management in their Supply Chain, Gestion, 2021. [Online]. Available: https://gestion.pe/economia/el-66-de-empresas-en-el-pais-tiene-un-nivel-de-gestion-incipiente-en-su-cadena-de-suministros-nndc-noticia/

[6] Gastón Guillermo Suárez Gallegos, and Polet Denisse Cárdenas Miranda, "Inventory Turnover and its Impact on Cash Flow," *Latin American Economic Observatory Journal*, Ecuador, 2017. [Google Scholar] [Publisher Link]

[7] Pradeep Kumar Shetty, and C. Raghavendra Kamath, "A Study of Inventory Management at Manufacturing Industries in Rural India," *International Journal of Mechanical and Production Engineering Research and Development*, Karnataka, India, vol. 9, no. 1, pp. 73-80, 2018. [Google Scholar] [Publisher Link]

[8] Wisam AL-Dulaime, and Walid Emar, "Analysis of Inventory Management of Laptops Spare Parts by using XYZ Techniques and EOQ Model - A Case Study," *International Journal of Scientific and Technology Research*, vol. 8, no. 10, pp. 3766-3774, 2019. [Google Scholar] [Publisher Link]

[9] Usman Ali et al., "Improved MRO Inventory Management System in Oil and Gas Company: Increased Service Level and Reduced Average Inventory Investment," *Sustainability*, vol. 12, no. 19, pp. 1-19, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] Felix Weidinger, "Picker Routing in Rectangular Mixed Shelves Warehouses," *Computer & Operations Research*, vol. 95, pp. 139-150, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[11] Elia Oey, and Maulana Nofrimurti, "Lean Implementation in Traditional Distributor Warehouse - A Case Study in an FMCG Company in Indonesia," *International Journal of Process Management and Benchmarking*, vol. 8, no. 1, pp. 1-15, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[12] Ram Babu Verma, and Sanjay Kumar Jha, "Implementation of 5S Framework and Barriers modelling through Interpretive Structure Modelling in a Micro Small Medium Enterprise," *International Journal of Recent Technology and Engineering*, Maharashtra, India, vol. 8, no. 3, pp. 7016-7017, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ajay Johnson, Syamjith Prasad, and Ashok Kumar Sharma, "Manufacturing Lead Time Reduction in a Scaffold Making Industry using Lean Manufacturing Techniques - A Case Study," *International Journal of Mechanical Engineering and Technology*, vol. 8, no. 2, pp. 137-148, 2017. [Google Scholar] [Publisher Link]

[14] Pablo Viveros et al., "Slotting Optimization Model for a Warehouse with Divisible First-Level Accommodation Locations," *Applied Sciences*, Switzerland, vol. 11, no. 3, pp. 1-30, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] D. Wu et al., "Vehicle Routing Problem with Time Windows using Multi-Objective Co-Evolutionary Approach," *International Journal of Simulation Modelling*, Viena, Austria, vol. 15, pp. 742-753, 2016. [Google Scholar] [Publisher Link]

[16] Vasiliki Kapou et al., "An Innovative Layout Design and Storage Assignment Method for Manual Order Picking with Respect to Ergonomic Criteria," *Logistics*, Basilea, Suiza, vol. 6, no. 4, pp. 1-21, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mehdi Keshavarz Ghorabaee et al., "Multi-Criteria Inventory Classification using a New Method of Evaluation Based on Distance from Average Solution (EDAS)," *Informatica: An International Journal of Computing and Informatics*, vol. 26, no. 3, pp. 435-451, 2015. [Google Scholar] [Publisher Link]

[18] I.M.D.P. Asana et al., "Inventory Control using ABC and Min-Max Analysis on Retail Management Information System," *Journal of Physics: Conference Series*, Bali, Indonesia, vol. 1469, no. 1, pp. 1-10, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] Milan Jemelka et al., "ABC Analyses with Recursive Method for Warehouse," 2017 *4th International Conference on Control, Decision and Information Technologies (CoDIT)*, Barcelona, Spain, pp. 960-963, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[20] Thanichkarn Phupattarakit, and Parames Chutima, "Warehouse Management Improvement for a Textile Manufacturer," *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)*, Tokyo, Japan, pp. 235-239, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[21] Jenny Gutierrez Lopez, Alvaro Freile, and Sofia Lopez Iglesias, "Reduction in Picking Times Orders for Delivery in a National Distribution Center: A Case Study," *17th LACCEI International Multi-Conference for Engineering, Education, and Technology*, Montego Bay, Jamaica, pp. 24-26, 2019. [Google Scholar] [Publisher Link]

[22] Johanna Rodríguez-León, and Mateo Pachón-Rincón, "Forecast in Planning, a Case of Study in a Distribution Company of the Pharmaceutical Sector," *Revista UIS Ingenierías*, vol. 20, no. 4, pp. 59-78, 2021. [CrossRef] [Publisher Link]

[23] Jente Van Belle, Tias Guns, and Wouter Verbeke, "Using Shared Sell-through Data to Forecast Wholesaler Demand in Multi-Echelon Supply Chains," *European Journal of Operational Research*, Brussels, Belgium, vol 288, no. 2, pp. 466-479, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] G. Sudheer, and A. Suseelatha, "Short Term Load Forecasting using Wavelet Transform Combined with Holt-Winters and Weighted Nearest Neighbor Models," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 340-346, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[25] Qing-Zhou Wang et al., "Waste Tire Recycling Assessment: Road Application Potential and Carbon Emissions Reduction Analysis of Crumb Rubber Modified Asphalt in China," *Journal of Cleaner Production*, vol. 249, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[26] Umamaheswaran Praveen, Ganjeizadeh Farnaz, and Ghasib Hatim, "Inventory Management and Cost Reduction of Supply Chain Processes using AI Based Time-Series Forecasting and Ann Modeling," *Procedia Manufacturing*, vol. 38, pp. 256-263, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[27] R. Nigah, M. Devnani, and A.K. Gupta, "ABC and VED Analysis of the Pharmacy Store of a Tertiary Care Teaching, Research and Referral Healthcare Institute of India," *Journal of Young Pharmacists*, vol. 2, no. 2, pp. 201-205, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[28] Sandeep Kumar Panda, and Sachi Nandan Mohanty, "Time Series Forecasting and Modeling of Food Demand Supply Chain Based on Regressors Analysis," *IEEE Access*, vol. 11, pp. 42679-42700, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[29] Byung Soo Kim, and Jeffrey S. Smith, "Slotting Methodology using Correlated Improvement for a Zone-Based Carton Picking Distribution System," *Computers & Industrial Engineering*, vol. 62, no. 1, pp. 286-295, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[30] Cristhian Alvarez et al., "Warehouse Model to Increase the OTIF by Applying BPM and Lean Warehousing in a SME in the Footwear Sector," *Proceedings of the 15th International Conference on Industrial Engineering and Operations Management*, Singapore, pp. 1-7, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[31] Adithya Narayanan Rajesh, "Labor-Saving in Order Picking- A Real Time Study Advancing Lean Operations," *American Journal of Supply Chain Management*, vol. 9, no. 3, pp. 16-25, 2024. [Google Scholar] [Publisher Link]

[32] D. Battini et al., "Consignment Stock Inventory Model in an Integrated Supply Chain," *International Journal of Production Research*, vol. 48, no. 2, pp. 477-500, 2010. [CrossRef] [Google Scholar] [Publisher Link]

Appendix

Appendix 1 - Comparative matrix of the proposal vs. State of the Art

	Inventory Management Models (Literature mapping vs Contribution of this research)					
Criteria	**Inventory control using ABC and min-max analysis on retail management information system [20]**	**Minimization of Smashed Products in Sustenance Industries by Lean and Machine Learning Tools [29]**	**Improved MRO Inventory Management System in Oil and Gas Company: Increased Service Level and Reduced Average Inventory Investment [9]**	**An Innovative Layout Design and Storage Assignment Method for Manual Order Picking with Respect to Ergonomic Criteria [18]**	**Optimizing Warehouse Management in Footwear Commercial Companies: A Case Study on Lean-BPM [13]**	**Proposed Model (Contribution of this research)**
Contribution	ABC model with min-max analysis to reduce overstock	Application of Machine Learning Models, 5S, MRP, and FEFO to Minimize Spoiled Products in the Food Industry	ABC-based (Q,r) inventory model for oil & gas plants to improve service levels and reduce inventory investment	Ergonomics-focused ABC-slotting model to redesign warehouse layout and improve manual picking performance in the retail sector.	The lean-BPM model integrates ABC, 5S, and Kardex to enhance warehouse operations and OTIF performance in	Forecasting Machine Learning Model with ABC analysis, slotting, EOQ, and 5S to reduce the overstock in the retail sector

			through cost optimization.		Peruvian footwear retail.	
Deficiencies	Does not consider external factors such as holidays, national events, or seasonal campaigns. Does not include prediction algorithms such as Machine Learning that could develop the order accuracy for low-rotation or seasonal products	Machine learning is limited to procurement tasks. Other lean tools are not considered in the study. 5S is applied only in warehouse operations.	Demand modeling through Poisson (erratic demand) does not use ML or advanced forecasting algorithms that could capture more complex trends or patterns. Skip the application of 5S, slotting, or layout design to improve picking/receiving efficiency.	Does not include algorithms to anticipate peaks or future consumption behaviors. Does not monitor inventory volume, nor does it propose reordering or EOQ policies.	Demand forecasting techniques, such as machine learning, are not used to anticipate future needs. The study focuses on internal warehouse optimization, without addressing external aspects of the supply chain.	ERP systems are not integrated, representing a future opportunity once the organization increases its investment capacity.
Phase 1: Inventory Classification - Engineering Tool: Multi-criteria ABC - Implementation Area: Warehouse	Engineering Tool: ✓	Engineering Tool: ✗	Engineering Tool: ✓	Engineering Tool: ✓	Engineering Tool: ✓	Engineering Tool: ✓
	Implementation Area: ✓	Implementation Area: ✗	Implementation Area: ✓	Implementation Area: ✓	Implementation Area: ✓	Implementation Area: ✓
	Sector: ✓	Sector: ✗	Sector: ✗	Sector: ✓	Sector: ✓	Sector: ✓
	Problem: ✓	Problem: ✗	Problem: ✗	Problem: ✗	Problem: ✓	Problem: ✓
Phase 2: Demand Forecasting - Engineering Tool:	Engineering Tool: ✗	Engineering Tool: ✓	Engineering Tool: ✗	Engineering Tool: ✗	Engineering Tool: ✗	Engineering Tool: ✓
	Implementation Area: ✗	Implementation Area: ✓	Implementation Area: ✓	Implementation Area: ✓	Implementation Area: ✓	Implementation Area: ✓
	Sector: ✓	Sector: ✗	Sector: ✗	Sector: ✓	Sector: ✓	Sector: ✓

Machine Learning - Implementation Area: Supply Chain Management	Problem:	✗	Problem:	✗	Problem:	✗	Problem:	✗	Problem:	✗	Problem:	✓
Phase 3: Inventory Optimization - Engineering Tools: EOQ, 5S, Slotting - Implementation Area: Supply Chain Management	Engineering Tool:	✗	Engineering Tool:	✓	Engineering Tool:	✓	Engineering Tool:	✓	Engineering Tool:	✓	Engineering Tool:	✓
	Implementation Area:	✗	Implementation Area:	✗	Implementation Area:	✓	Implementation Area:	✓	Implementation Area:	✓	Implementation Area:	✓
	Sector:	✓	Sector:	✗	Sector:	✗	Sector:	✓	Sector:	✓	Sector:	✓
	Problem:	✗	Problem:	✓	Problem:	✗	Problem:	✗	Problem:	✓	Problem:	✓
Total		**6**		**4**		**5**		**8**		**10**		**12**