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Original Article

Enhancing Service Levels in a Peruvian Beverage SME: An Innovative Model Integrating Machine Learning and 5S Methodology

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Abstract *- In Peru, the food and beverage services sector shows constant annual growth and a demand experiencing significant monthly variations. However, SMEs in this sector face recurring problems due to their low levels of preparedness, making demand fluctuations a latent threat. Food and beverage service SMEs suffer from inadequate inventory management, inaccurate supply planning and a lack of process optimization, which leads to a low level of On Time in Full (OTIF) deliveries. This is detrimental to an SME, as customer satisfaction is crucial in this sector. Due to this, the present study proposes an innovative Lean Management model that integrates 5S tools and Machine Learning to increase OTIF in a Peruvian beverage service SME. The research focuses on the Milk Tea and Smoothie product lines, which exhibited stockouts and high preparation and stock review times through analysis and diagnosis. The proposed model results in a reduction of 75.98% in the total cycle time of an order. Additionally, the implementation of Machine Learning helped reduce stockouts by providing a more accurate supply forecast, improving forecast error by 19.72% and 38.71% for tapioca and milk, respectively. These indicators led to a 51.42% increase in OTIF. Thus, this management model effectively innovates by adapting tools often used for manufacturing and production to the services sector, thereby achieving outstanding results in both efficiency and customer satisfaction.*

Keywords *- Machine learning, Lean management, Beverage industry, Inventory management, Enterprise resource planning*.

1. Introduction

As a result of the post-pandemic economic recovery, the food and beverage service sector has grown significantly, and within this sector, the beverage service subsector has been no exception. According to INEI, the subsector experienced an average annual growth of 42.58% and 16.15% in 2022 and 2023, respectively. [1] Additionally, this subsector is comprised of local medium or small-sized enterprises (SMEs). SMEs, while crucial for economic development, tend to be managed by workers with incomplete secondary education, which affects managerial decision-making. [2] It is estimated that demand for the subsector will grow due to its dynamism, aiming to reach pre-pandemic sales levels. However, the fluctuations in the beverage service subsector, in addition to the low preparedness to leverage the benefits, constitute a recurring problem in meeting the service level required by consumers. [3] According to multiple authors, deficiencies in the sector are caused by issues such as improper demand planning, inefficient inventory management, and inadequate storage of supplies. [4] These issues, along with the disorganization of areas and the long service times they create, are the main reasons for the decline in consumer satisfaction. [5-6] The case study was conducted at a Peruvian SME in the food and beverage service sector, where the main issues were inefficient inventory management and high customer service times. The former occurs due to the inability to correctly predict fluctuating demand and purchase supplies accordingly. Another identified problem is the lack of organization, order, and the possession of obsolete items. These problems were identified through information provided by the company about customer complaints regarding product availability and long preparation times. The latter is because sometimes store employees must purchase the missing products during preparation times, which delays the service. This study focuses on these issues by addressing the following questions:

How does the implementation of 5S and Machine Learning improve OTIF for an SME in the food and beverage service sector?

In this case, the indicator demonstrating the improvement in these issues is OTIF (On Time In Full). The On Time In Full delivery rate measures the percentage of complete orders that were delivered at the right time. This explains how stockouts and high service times impact consumer satisfaction and operational success. [7] Therefore, OTIF is a very important indicator in all manufacturing and service companies as it determines whether the company is truly meeting customer expectations. The studied SME loses an average of S/.3,000 daily in opportunity costs due to the loss of customers resulting from the unavailability of products and high service times. These are caused by the need to purchase supplies during preparation times. Consequently, the OTIF delivery rate for the SME is 51.65%, while the industry standard is 92%. This low rate is attributed to lower performance in its components; the SME has a low on-time delivery rate, as it reflects the ability to deliver orders within the promised time frame and a low fill rate. The latter measures customer demand, which can be met directly from an available inventory. Both issues are the consequence of high service times and inefficient inventory management.

This research is important as it demonstrates that Lean Management tools, such as 5S and Machine Learning, can help mitigate the problems in SMEs from the food and beverage service sector. 5S is a structured methodology that follows five Japanese principles: Seiri focuses on removing unnecessary items from the workspace. Seiton consists of organizing items for optimal efficiency. Seiso involves maintaining cleanliness, Seiketsu establishes standardized practices to keep processes consistent, and Shitsuke ensures these practices are sustained over time through discipline and control. On the other hand, Machine Learning applies algorithms to learn from historical data and predict demand patterns with high precision. This is done considering the OTIF's improvement, as its values determine whether customer deliveries are adequate, on time, and in correct quantities.

The first problem, inefficient inventory management, speaks of the inadequate procurement of supplies. For this, Machine Learning has been proposed, as well as demand forecasting models such as ARIMA, Holt, moving average, and other statistical models were evaluated to determine the most suitable through an error test. This test involves the MAPE, Mean Absolute Percent Error, a metric that measures the accuracy of a forecasting method by calculating the average absolute percentage difference between predicted and actual values. The other problems are the inefficient distribution of work areas, machines, and tools, as well as the possession of unused items, which are addressed using 5S. This tool will help with the organization, order, and cleanliness of the work area and storage.

The reviewed literature presents cases of lean tool implementation across various sectors. Lean management tools are often directed towards cost reduction, as it has been proven to ensure high productivity in industries. [8] Moreover, most lean methodology is applied in manufacturing companies due to their more tangible and repetitive activities, which simplify measurement and control. Even so, there's a consensus that the service sector is becoming increasingly important in the world. [9] In this sense, authors have implemented 5S models and machine learning in the food service sector with the aim of reaching maximum efficiency; however, this often translates to waste minimization rather than improving satisfaction. Many authors agree on the effectiveness of lean tools such as 5S, Kaizen, Poka Yoke, etc., as they are successfully used to minimize errors, cycle times, and disorganization, as well as optimize storage allocation. [10] Furthermore, Machine Learning is used to estimate the stock quantity required to reduce food waste and inventory turnover. [4,11] The previous studies demonstrate that lean tools have a positive impact on reducing cycle times, improving organization and optimizing storage allocation. Meanwhile, Machine Learning aids with agility to meet fluctuating demands through the estimation of stock required to manufacture goods [11]. Despite service level being the sector's key driver, current literature on lean management in food and beverage services is not focused on the impact these changes may have on customer satisfaction. [8-9] This gap in the literature leads to question the benefits that could be seized from lean tools to improve, not only reduce costs but also improve service level and, in consequence, gain a loyal consumer base and increase revenue.

The literature review reveals both application and empirical gaps. Firstly, an application gap was identified because the literature presented several studies with models applied to sectors such as the food industry and clothing manufacturing. Although, in some studies, the tools remained the same, there was a gap in the application for the food and beverage service sector. On the other hand, the empirical gap identified consists of the problem addressed in the case studies. Even though some use Machine Learning and others use 5S and other lean tools, they have not implemented a model to address OTIF (On Time in Full) delivery rates. Studies combining both tools often focus on cost reduction and waste minimization. [8-9] The research is structured into different sections. Section 2 outlines the state of the art based on the reviewed literature, divided into typologies based on the tools used (5S and demand forecasting) and the beverage service sector or similar. Section 3 presents the research contribution, including the gap research foundation, detailing the findings from the literature review. Following this, the same section includes the proposed model construct, details (showing the implementation of methodologies in the sector to address the problem), the process followed, and indicators. Section 4 presents the results and improvements. Sections 6 and 7 present the conclusion of this research and potential future studies.

2. State of the Art

This research is supported by 40 scientific articles selected for their high validity in the field of study. These articles are dated between 2018 and 2024 to ensure contemporaneity. The focus of the research is on improving delivery in the services sector.

Table 1. Research procedure

Steps	Description
Establish purpose and objectives	Review articles regarding the integration of lean, 5S and demand forecasting favoring OTIF.
Define keywords	Keywords are defined to limit the focus to articles with similar goals.
Indicate period	Only documents published within the last eight years are considered to ensure relevance.
Journal revision	The articles must be published in journals indexed in Scopus and ScienceDirect, among others.
Synthetize, study and analyze	The improvements achieved in SMEs should be presented based on the article, review results, and sector analysis.

However, other sectors are also considered, as the main issues analyzed are not limited to this sector. The databases reviewed are Scopus, Science Direct, and ACM Digital Library, which provided valuable information on the tools evaluated. The research procedure is detailed in Table 1. Several authors propose methodologies based on Lean to optimize processes in a supply chain, either to improve cost efficiency, time or performance. According to the literature review, the following typologies were considered.

2.1. Lean Management in the Beverage Services Sector and/or Similar

Issues such as fluctuating demand and inefficient inventory in the food and beverage service sector can be addressed using Lean tools. Various authors suggest that implementing these tools enhances productivity and service quality, reduces costs, and increases the company's competitiveness in the market. This is because Lean methodology focuses on process optimization, which leads to increased customer satisfaction. [8-9] However, the effectiveness of these tools is not sector-specific, as they can be applied to companies of various sizes and industries. [2,10] For instance, in a shoe repair shop, issues with untimely and incomplete orders persisted, and a study demonstrated the positive impact of Lean on the entire production cycle, resulting in improved OTIF. On the other hand, a study of a small food service company identified a need for better demand forecasting control, highlighting the benefits of forecasting tools and 5S, among others. [4]

Lean methodology encompasses various tools aimed at process optimization, such as 5S, work standardization, Kardex, SLP, and demand forecasting. The selection of tools, according to most authors, involves applying them to specific problems within the company. For instance, while some studies use 5S and Kardex to organize inventory, others apply 5S, work standardization, and SLP to reduce unnecessary routes. Each approach proves effective in addressing specific aspects of the problem. However, this research has identified an overlap in the benefits provided by these tools, as some tools can address multiple issues simultaneously. Despite the variations in models across articles, there is consensus on the benefits of 5S. Additionally, demand forecasting is crucial for addressing planning issues. [4]

Although there is extensive literature on the application of these tools, cases of their implementation are predominantly focused on manufacturing and production sectors rather than on food and beverage services. [9] Furthermore, existing studies in this sector often aim at minimizing waste and reducing costs. There are limited examples of Lean implementation aimed at improving customer satisfaction in the specified sector. Additionally, articles from similar sectors often employ multiple tools to solve a problem, which can complicate execution. Consequently, there is limited scientific basis for establishing a precedent in improving OTIF in the food and beverage service sector using 5S and demand forecasting. Therefore, it is essential to analyze the impact of applying these Lean tools—5S and demand forecasting—on the food and beverage service sector.

2.2. Application of Demand Forecasting and Machine Leaning to Reduce Stockouts

Addressing issues prevalent in both manufacturing and service industries, one common challenge is inventory planning, which requires accurate demand forecasting. Errors in hourly demand predictions can lead to significant financial and customer losses. [12] Inadequate demand estimates can result in lost sales or excessive inventory, increasing operational costs. Consequently, effectively meeting market demand is crucial for maintaining competitiveness, as all operations and supply chains depend on accurate demand forecasts. [13] Achieving high precision in forecasting relies on data. Therefore, it is essential for it to be updated with new technologies and required capabilities. [12]

There are several forecasting methods used for demand prediction, such as Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Networks (ANN), and Holt-Winters. These methods are evaluated by comparing their performance using the Mean Absolute Percentage Error (MAPE). The results reveal which method best fits the demand to be predicted. [12] These forecasting models are valuable assets for improving decision-making, minimizing waste, and maximizing the number of orders delivered. [11] The stages of demand forecasting can be summarized as follows: the first stage involves processing the exact data provided by the company; the second stage involves applying forecasting using methods like ANN, Holt-Winters, and ARIMA. In the final stage, the results are analyzed using all models, and they are compared through error metrics (MSE and MAPE%). [12] To test the duality between forecasting methods and short-term demand prediction performance, various forecasting models are often employed, such as time series models and causal models. Time series models begin by analyzing a time series to identify patterns, trends, and cyclicality, then replicate results to predict future values aligned with the environment. Causal models, on the other hand, use exogenous variables to help categorize the environment and predict a target variable. These models are designed to improve operations for a given time frame. For instance, if the forecast is made at time t, the goal is to predict demand for $t + 1$, in essence, the next day. [11] While this approach provides valuable information, there is little scientific evidence of its application in the services sector, making it necessary to conduct research on demand forecasting and machine learning within this industry.

2.3. Application of 5S Tools for Inventory Management

As previously mentioned, the 5S tool is part of the Lean Management methodology, which focuses on optimizing and increasing process efficiency. It helps create an optimal work environment for task execution. Various studies highlight that 5S is one of the essential tools for companies pursuing continuous improvement. It can bring significant organizational changes, particularly in warehouses, by reducing unnecessary travel, eliminating wasted time and space, and improving productivity, quality, work climate, and workplace safety. [14] Additionally, 5S can be used in warehouses with many SKUs to define their space and location, helping to organize, minimize waste, reduce work stress, and streamline processes. [7]

One of the most frequent problems in warehouses of manufacturing companies in Peru is the delivery of non-conforming products, which impacts on-time delivery and perfect orders, directly impacting the OTIF. This key metric measures timely and complete deliveries. [15] Implementing the 5S tool can help operators create an optimal working environment in warehouses by improving visual management. This reduces the time needed to locate products and eliminates process errors by adding identification labels. Additionally, the tool simplifies and speeds up inventory counts, leading to an increase in perfect and complete orders, thus improving OTIF performance. [14]

By using a Lean service quality approach and tools such as the 5S methodology, process documentation, and standardized work methods, companies can ensure comprehensive development of functions between the administrative and operational parties. This results in effective communication, contributing to the continuous improvement of operational activities. Given that 5S enhances communication between administrative and operational areas and increases perfect and on-time deliveries, it also helps reduce losses from non-conforming orders. [16] Additionally, 5S reduces losses in selected processes within manufacturing companies by implementing a step-by-step technique to improve operational efficiency by eliminating unnecessary movements and waiting times dedicated to searching for tools, which are labeled and organized to prevent mistakes and reduce losses. Although the application of 5S in warehouses is well-developed in various sectors, there is limited information on its use in the sector under study, making it necessary to demonstrate the validity of its benefits.

2.4. Application of 5S Tools for Space Optimization

The Lean 5S tool is widely used to improve resource efficiency, organization, standardization, and medium-to-long-term commitment. Large companies have implemented it to reduce waste, but for small and medium-sized enterprises (SMEs), it also improves overall organization and order preparation times. [8] Despite its common use focused on cleanliness and constant order, the 5S tool offers multiple benefits, including route reduction, inventory and equipment classification, and process standardization. It is also applicable across various sectors. One of the main advantages of 5S is the proper distribution of space through classification, organization, and order. Additionally, cleanliness, standardized processes, and discipline help reduce activity times. [18] Some studies suggest that the use of 5S enhances process agility and optimization by classifying areas, equipment, and supplies and eliminating non-value-adding activities that slow down order cycles. [19-20] The organization of elements, or Seiri, based on an analysis of employee movements, helps determine the necessary placement of each item. [21] Classifying them accordingly results in shorter activity times and increased customer satisfaction due to faster service. Another benefit of 5S is the role it plays in fostering discipline and work habits within the company. Its continuous improvement philosophy seeks to engage employees in the company's development. [22]

In the food and beverage service sector, speed of service is critical to customer satisfaction. Long wait times or receiving incomplete products diminish the perceived value and reduce the likelihood of customer return. [8] Therefore, reducing service time is essential. However, there is no evidence of 5S implementation to reduce movements in the workspace of a beverage service SME. Hence, promoting the use of the Lean methodology in the sector is necessary to enhance the efficiency of order preparation and customer service cycles.

3. Contribution

3.1. Foundations

Based on an exhaustive literature review, the tools used to increase OTIF were determined. The aim was for these tools to address the root causes identified, such as high service times, poor demand forecasting, and inefficient inventory management. Considering the selected articles, an innovative model was developed comprising 5S and Machine Learning tools, with the distinction being the implementation sector: a small or medium-sized enterprise (SME) in the food and beverage service sector, and the focus on OTIF to improve consumer satisfaction. Additionally, the proposed model includes the use of Machine Learning to forecast the daily demand for the main product, thereby determining the required daily preparation of the supply. Similarly, the 5S tool was applied not only in the company's storage area but also in the product preparation area, which is visible to customers.

Through an analysis of existing models and a study of the problem in the SME, the phases of the proposed model were determined: inventory management, supply planning, and process optimization, which encompass the main issues of the case study and the selected literature. Six criteria were established to compare the articles with this research, as shown in Table 2.

Table. 2 Comparative matrix with literature review

Criteria	**Lean management approach to reduce waste in HoReCa food services. [9]**		**Minimization of Smashed Products in Sustenance Industries by Lean and Machine Learning Tools. [4]**		**Machine learning models for short-term demand forecasting in food catering services: A solution to reduce food waste [11]**		**Production Management Model Based on SLP, 5S, and Standardized Work Tools to Increase OTIF Rate in a Shoe Repair Shop.**		**Implementation of Lean and Logistics Principles to Reduce Non-conformities of a Warehouse in the Metal working Industry. [15]**		**Proposed Model (Contribution of this research)**	
Contribution	Lean model with 5S, kaizen, and VSM to reduce food waste		Machine Learning Model, 5S, MRP, and FEFO to Reduce Deteriorated Products in the Food Industry		Machine learning model to reduce waste with demand forecasting in meal services		SLP, 5S, and SW model to improve OTIF in footwear services		Lean model with 5S and VSM to reduce non-conforming deliveries in the warehouse of the metalworking sector		Machine Learning model with daily forecasting and 5S to increase OTIF in the food and beverage service sector	
Deficiencies	Requires accurate demand forecasting Does not implement preparation design aimed at mitigating demand fluctuations		Does not explore the use of other lean tools 5S focused on the warehouse Machine Learning only for procurement		Does not explore the use of additional tools Used only for provisioning		Do not use demand forecasting to estimate required supplies and minimize space occupancy.		5S focused on the warehouse Does not use demand forecasting to estimate inputs		Does not explore the use of additional Lean tools. Long-term monitoring is not conducted.	
Phase 1: Inventory Management - Engineering Tool: 5S - Implementation Area: SME Warehouse - Sector:	Engineering Tool:	✓	Engineering Tool:	✓	Engineering Tool:	X	Engineering Tool:	✓	Engineering Tool:	✓	Engineering Tool:	✓
	Implementation Area:	✓	Implementation Area:	✓	Implementation Area:	X	Implementation Area:	✓	Implementation Area:	✓	Implementation Area:	✓
	Sector:	✓	Sector:	X	Sector:	✓	Sector:	X	Sector:	X	Sector:	✓
	Problem:	X	Problem:	X	Problem:	X	Problem:	✓	Problem:	✓	Problem:	✓

Food and Beverage Services - Problem: OTIF												
Phase 2: Supply Planning - Engineering Tool: Machine Learning - Implementation Area: Ware house and Preparation Area - Sector: Food and Beverage Services - Problem: OTIF	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 3: Process Optimization - Engineering Tool: 5S - Implementation Area: SME Preparation Area - Sector: Food and Beverage Services - Problem: OTIF	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		**7**		**4**		**4**		**6**		**6**		**15**

The first two criteria, contribution and deficiencies, aim to describe the selected models and establish the thematic gaps they present. The remaining criteria are compared against the present paper to state attributes the reviewed literature may or may not have focused on. A fundamental criterion was the engineering tool; in the matrix, the tool applied by each article is compared with those of this study, namely 5S and Machine Learning. The fourth and fifth criteria chosen are the area and sector where the model will be implemented. The purpose of analyzing these is to identify a gap in the application of the tools. Finally, the problem addressed by each article is evaluated, as it is crucial to recognize the primary objective or problem that each model aims to solve, as this determines the focus each author gives to their proposal.

The evaluation of criteria such as contribution and engineering tools highlighted that the joint application of tools like 5S and Machine Learning is limited. Similarly, there is no scientific evidence that this model has been implemented in the food and beverage service sector; Carbajal-Vásquez and other authors present a similar model applied in the food industry, indicating an application gap. [3] Additionally, the matrix demonstrates an empirical gap, as although the tools are used in the service sector, they do not aim to address the problem of increasing OTIF, indicating a lack of research on this topic. Despite the importance of customer satisfaction in the food and beverage service sector, authors such as Gladysz and Rodrigues focused their articles on waste reduction, like most authors studying the sector. [9,11] Gladysz asserts that future work should focus on developing accurate demand forecasting and highlights the need to design food preparation to withstand demand fluctuations [9]. Thus, it can be stated that tools like Machine Learning are necessary in the food and beverage service sector for product preparation areas.

However, multiple authors show that its primary implementation lies in supply provisioning, so its application area is limited to storage and not preparation zones, as evidenced in the comparative matrix. Similarly, the implementation area of the 5S Lean tool is typically storage; the application of 5S to preparation areas in customer service zones is limited. Based on the mentioned gaps, both in the implementation of the model in the sector and in the application of tools focused on the problem of studies, an innovative model is proposed to address stockouts and high order delivery times. This novel model, involving the 5S and Machine Learning tools, offers a solution to the OTIF problem in a new sector where customer satisfaction is paramount: the food and beverage service sector.

3.2. Construct of the Proposed Model

The proposed innovative model consists of a comprehensive service management model aimed at solving supply planning issues to eliminate stockouts, inventory management to reduce stock review times, and process optimization to decrease order delivery times. Although these difficulties lead to low OTIF (On Time In Full), a recurring problem in the sector, there is a thematic gap in the research, as articles implementing Lean in the current sector are limited. Moreover, what is even more alarming is that these articles fail to address the OTIF problem. Figure 1 dynamically illustrates the composition of the proposed model for the food and beverage service sector. This diagram presents the model as a timeline where the input is the low OTIF level in the SME, and the output is a high OTIF, resulting from the implementation of the Diagnosis, Intervention, and Validation components. The novelty of the model lies in the joint implementation of 5S and Machine Learning to address OTIF in a different sector where customer satisfaction is essential.

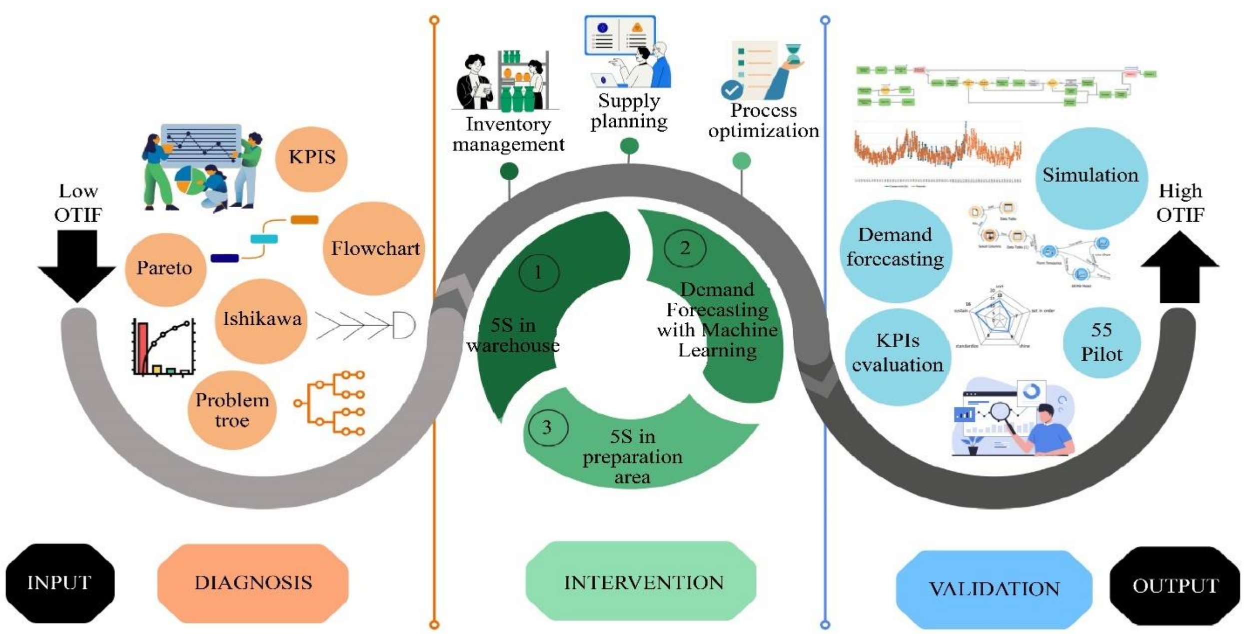

Fig. 1 Proposed innovative model

3.3. Component Details

In the initial stage, a diagnosis of the preliminary situation was conducted to determine the problem, its root causes, the KPIs, and the technical gap according to the sector. Various engineering tools were used for this purpose. Initially, a flowchart was created outlining the processes of the company under study. After evaluating each process individually, an Ishikawa diagram was constructed, identifying the main problems evident from the evaluation. This Ishikawa diagram presents five phases identified as significant in the company: environment, personnel, methods, inputs, and machines.

Based on the improvement opportunities reflected in the diagram, Lean management tools were proposed to improve in-store service times and reduce stockouts. Thus, KPIs suitable for evaluating the problem in the company's supply chain are outlined. The main KPI characterizing the problem is the On-Time-In-Full delivery rate (OTIF), which is composed of the Fill Rate and On-Time Delivery rate (OTD). This measures the probability of meeting demand without causing stockouts and within appropriate time frames. Additionally, KPIs that indicate the impact of the proposed improvement are examined. Consequently, the total order cycle is analyzed to measure OTD, forecast error, and inventory duration to evaluate stockouts and, consequently, the rate of complete deliveries. Data collection was conducted to determine the business' KPIs. The SME studied was selected due to the availability of the data. Nevertheless, ethical considerations such as data privacy and transparency were thoroughly addressed. To ensure this, the study anonymized sensitive information. Moreover, maintaining transparency in reporting findings to avoid the misrepresentation of results was imperative. On the other hand, the pilot included training and extensive information to minimize the stress of employees' workloads.

The data collection included historical sales reports for the last 2 years and a compilation of weekly and monthly purchases of inputs that typically experience stockouts, such as whole milk, and the frequency of these stockouts necessitating extra purchases. Furthermore, a time study was conducted to measure the cycle times in the SME. Based on this, the indicator values were identified for the company before applying the tools. Subsequently, the company's KPIs were compared with industry standards obtained through an exhaustive analysis of information. In the second stage, the selection of tools was carried out. The selected articles for this research provided important contributions, as they helped us understand and substantiate the tools used for problem resolution. The authors presented Lean tools such as 5S, Poka Yoke, and Kaizen, among others, and forecasting tools, highlighting their positive impact on the results of the companies analyzed. [4] However, it is noted across articles that, regardless of the sector analyzed, these tools are successful in various fields. The authors indicate that, in a process of continuous improvement, it is essential to implement the 5S tool. [24] Additionally, several articles used demand forecasting to mitigate fluctuation risks; however, there is variation in the methods used. While some use Holt and regressions, others use Machine Learning and measure ARIMA and SARIMA with Python. [4, 24] On the other hand, Acevedo-Aybar and other authors indicate that Lean tools have a significant impact on improvement and do not require a large investment. [2] Therefore, it is considered that the contributions of the articles allow for improvements in SMEs without a highly required capital. Furthermore, some articles conclude that Lean techniques are necessary for inventory management improvement, which is related to another research objective. [25]

According to the literature review, the 5S method and demand forecasting improve efficiency in a supply chain. The 5S method aims to optimize service by improving the cleanliness, order, and organization of inputs, tools, and machines, as well as eliminating situations and objects that cause delays or inefficiencies. This is a solution to inventory management problems, as the SME in the case study produces an excess of unwanted items. Additionally, the demand forecasting method improves the company's flexibility to changes in demand through tools such as historical sales data analysis. Once the tools were selected, the improvements were implemented. Initially, preliminary preparation for the 5S pilot was conducted through a literature review of its application in various sectors. Based on this and knowledge of 5S manuals, planning for the pilot was developed. The first step of 5S is Seiri (Sorting), in which items were categorized as unnecessary—such as waste, obsolete items, or items that needed to be moved to another location—and necessary. The unnecessary items were tagged with a Red Tag for classification and then removed from the work area and store warehouse, which were the studied areas. After discarding unwanted items, visual schemes were created to organize the spaces, the second S of the tool. This simplified the labeling and order of work and storage areas. Additionally, an area for waste segregation and storage was defined.

The third S involves cleaning the work area. For this, responsibility sheets and checklists were created to confirm compliance. For standardization, the fourth S, descriptive documents of standardized processes were created. This, along with continuous training, helps maintain order in processes and instils discipline to follow them. Finally, the fifth S is discipline. For this, evaluations and audits of the process were conducted, providing feedback to employees. Tracking sheets and employee surveys were also created to confirm compliance again. For the application of the second tool, demand forecasting was evaluated through its percentage error. Various metrics can evaluate forecasting errors, including MSE, MAE, and MAPE. However, like many authors, the analysis is based on Mean Absolute Percentage Error (MAPE). This is because, unlike other metrics, MAPE is represented as a percentage, which simplifies understanding without needing knowledge of previous units. Additionally, MAPE is the most used error for model estimation. [26] MAPE represents an error calculated by dividing the absolute error by the consumption. Absolute error refers to the difference between the actual consumption of a specific input and the forecast made using various methods.

There were two validation models used for forecasting input consumption: Minitab and Orange. Firstly, Minitab was used to create statistical models, measure their MAPE, and forecast future demand with a 95% confidence interval. Minitab is statistical software used for data analysis and is widely used in process improvement. In this, a time series analysis was conducted. A time series refers to a group of values that a quantitative variable acquires over a period. [27] On the other hand, machine learning was used through orange software to create an ARIMA model for forecasting consumption. Orange is an open-source data software that is built using the Python programming language. Python offers advantages such as speed, extensive libraries, and concise code. [27] This is the primary reason for choosing this software; another reason is that Minitab only allows forecasting up to 150 periods, whereas ample historical data was needed to enable the model to comprehend trends and seasonality.

The ARIMA model allowed real-time adaptability to fluctuations in demand through a regularly updated system. The model was trained on historical sales using Python libraries, where seasonality, trends, and other behavior could be considered to estimate a forecast. These, along with the input of new data, enable the model to learn from its variability. Moreover, the MAPE was calculated to compare the model against the previous statistical models, to ensure the accuracy of the model. This approach enabled the SME to maintain optimal stock and meet the preparation requirements to satisfy the customer demands. For this third stage, the validation model was presented using Arena software, which allows for validating the impact of various improvement tools. Thus, the development of the base or initial model was demonstrated, which aligns with the company's KPIs presented earlier. Additionally, the logic behind creating the model, its entities, completion, and modules for obtaining results was explained. Finally, the model with the implemented improvement was presented, along with its relation to the analyzed indicators. Additionally, the operational part of the process, including the 5S pilot implementation and demand forecasting, was presented. Arena software was used for the simulation. Initially, data provided by the company were considered, which allowed for determining a distribution for each time not requested by the simulation, including the time between customer arrivals, checkout time, order preparation, stock review, delay in purchasing extra supplies, and order delivery time. With these input times, the simulation of the process before improvements were conducted, and the results were found to match the actual times provided by the company. Once the initial model was validated, the model was created after the improvements were made, considering the input times that changed due to the improvements. It was evident that no extra purchases were made, even though the process was modeled in the simulation. The times and quantities of milk provisioning and daily tapioca preparation amounts were also included. With the output obtained from the simulation, both with and without improvements, comparisons were made to show significant improvements.

3.4. Process

Figure 2 shows a flowchart that outlines the process followed for implementing the model based on the details mentioned. This flow is divided into three parts, specifically determined by the components, and shows the sequence of steps taken in each part. Initially, in the diagnosis phase, information is collected, and problems and indicators are determined. Next, in the intervention phase, tools are determined, and the implementation of each tool is detailed. Finally, for validation, the initial and final process models are created in Arena, and outputs are analyzed to compare indicators and determine improvements. The following details are the four indicators analyzed to measure the SME's performance and the impact of the proposed model on improvement.

a. OTIF (On Time In Full):

$$OTIF = OTD \times Fill\ Rate \tag{1}$$

Various studies indicate that the proposed tools can increase the OTIF indicator by 18.6%. [25]

b. Inventory Duration:

$$Duración\ de\ inventario = \frac{Inventario\ medio}{Coste\ de\ las\ mercancías\ vendidas} \times 365 \tag{2}$$

Various studies state that the proposed 5S and demand forecasting model can increase inventory turnover by 117%, indicating an inventory duration of 6 days. [28]

c. Forecast Error (MAPE):

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \frac{|Z(t) - X(t)|}{Z(t)} \times 100\% \tag{3}$$

Multiple studies state that the proposed 5S and demand forecasting model reduces the indicator by 9.7%. [29]

d. Total Order Cycle:

$$Ciclo\ total\ de\ un\ pedido = \sum_{t=1}^{N} Tiempo\ de\ cada\ actividad \tag{4}$$

Various studies indicate that the proposed tools reduce the total order cycle time by 9 minutes with the proposed lean model. [30]

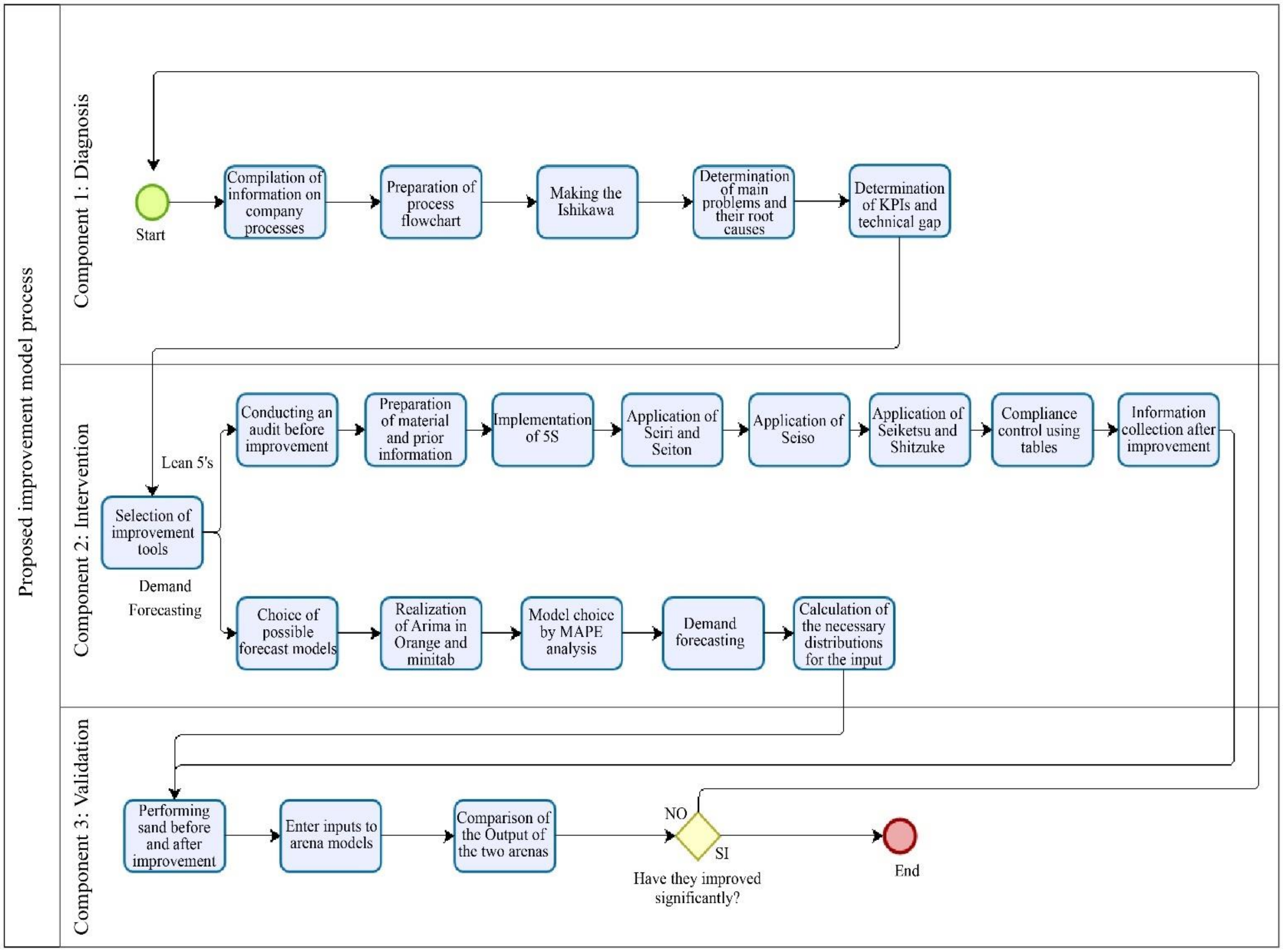

Fig. 2 Flowchart

4. Validation

4.1. Validation Scenario

To demonstrate the favorable results of the proposed improvements, a pilot plant and a simulation using Arena software were conducted as validation methods. The case study involved improving the OTIF (On-Time, In-Full) performance of a small food and beverage service enterprise. The pilot was established to collect data from the implementation of the tools. Each plan evaluated variables such as time and resources consumed to analyze the impact of the improvement proposal. Additionally, a simulation was used to validate the results and to confirm the effectiveness of the proposed model.

4.2. Initial Diagnosis

The company specializes in preparation and service, involving activities from supply management to customer service. The key issue is a low OTIF of 71.71%, below the industry average, resulting in daily economic losses of approximately S/.3,000 (approx. 826 USD) due to missed sale opportunities. The low OTIF is driven by late and incomplete deliveries, negatively impacting customer satisfaction. The root causes include a low On-Time-Delivery (OTD) caused by long order cycles and stock revisions; poor demand forecasting, with errors of 26.72% for tapioca and 45.71% for milk; and poor inventory management, with stock lasting less than 2 days for weekly-supplied milk and 0.21 days for daily-prepared tapioca. Figure 3 outlines the diagnosis and proposed tools to address each root cause.

4.3. Validation design

4.3.1. 5S Pilot Plan

To implement the 5S tool, the store and warehouse were identified as critical areas due to time lost by workers during stock revision and preparation. The pilot plan was conducted from April 22 to April 30, and its main goal was to reduce time spent locating products and create a more organized workspace, enabling workers to perform their tasks efficiently, as disorganization often leads to inventory or preparation errors.

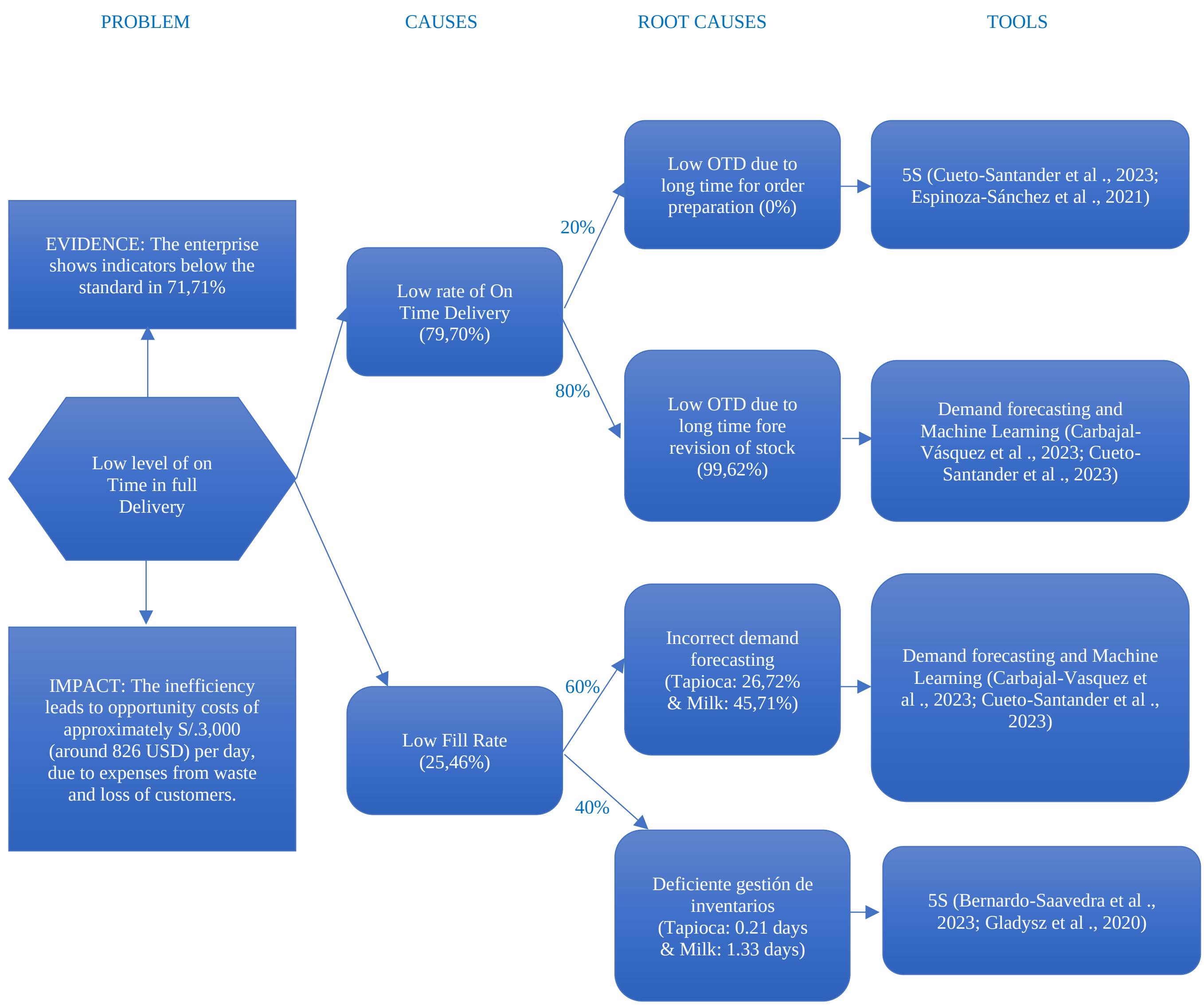

Fig. 3 Problem tree

Seiri (Sort)

The first S focuses on organizing and classifying items in key areas to add value to the customer. Materials that were not being used taking up space, and hindering workflow were identified, along with items that needed to be relocated or discarded. A control sheet and red tags were used to mark unnecessary, obstructive, defective, or obsolete items. This helped assess the condition of the workspace and storage area prior to the improvements.

Seiton (Set in order)

In this stage, supplies in the store and warehouse were classified into dry products, liquid products, filling ingredients, kitchen utensils, and cleaning items. A control sheet tracked each item's purpose based on the frequency of use, necessity, and observations. Shelves were labelled to make product searches easier, and items were arranged based on usage frequency, with the most used items placed near the preparation area to improve staff efficiency.

Fig. 4. Usage of red tags for classification

Table 3. Store before and after implementing Seiton

Before	After
	

Table 4. Delimitation of areas

Machinery areas	Workstations
	

Additionally, boundaries were set for areas housing the machines and tools stations for preparation, administrative, and cleaning purposes. Finally, work areas were clearly marked, including the store's preparation and pre-opening zones, the measurement area, and the delivery area. This is illustrated in Table 4.

Seiso (Shine)

A cleaning checklist was created, specifying the time of day for each task (before opening, during service, and at closing). This list was distributed among employees based on their shifts, facilitating cleanliness control through a schedule. To manage waste, it was segregated into three labelled bins: recyclable, non-recyclable, and organic. Additionally, checklists were introduced to ensure adherence to the cleaning schedule.

Seiketsu (Standardize)

In the fourth phase, a procedure was created to keep the store and warehouse organized, which was placed next to the lockers to ensure visibility and accessibility for all employees. A daily cleaning control sheet was introduced to continuously assess the condition of the first three S's. Additionally, a reminder poster outlining the 5S philosophy was displayed to ensure task compliance.

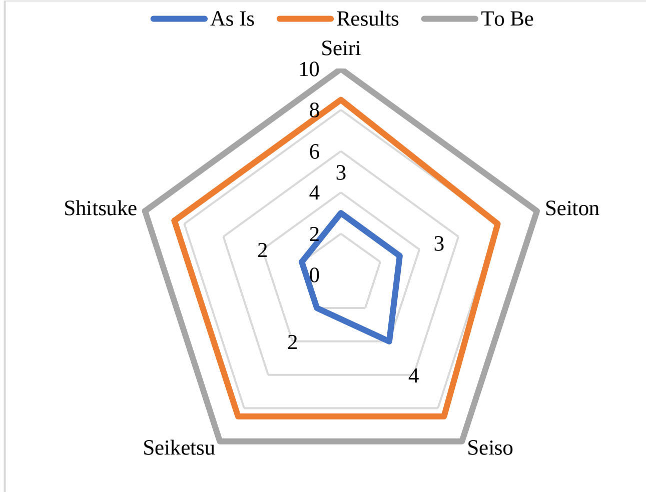

Fig. 5 Comparison before and after implementing 5S

Shitsuke (Sustain)

Finally, the staff was reminded of the phases of the 5S and the method to achieve the goal. To do this, a visible sheet was put up for everyone, indicating the meaning, objective, and steps to follow for the 5S. Based on this, a classification index was created for each S, which allowed a comparison of the initial state with the final audit results.

4.3.2. Simulation in Arena Software

The construction of the validation model in the Arena software is shown below. This software is used to simulate processes with real data and adjust to simulate improved levels in the case of inventory or input new data distributions in the case of time tests. This allows us to compare the process before and after improvements, which validates the impact of the proposed model. Additionally, the simulation runs in an established interval of time to gather various results, which are based on the time it lasts, and comparisons can be made between the initial and final process. Based on this, the development of the base model aligned with the company's KPIs is shown. The model with the improvements implemented and its relationship with the analyzed indicators is also included. The operational part of the process is also addressed, including the pilot implementation of 5S and demand forecasting. Figure 6 shows the diagram of the initial customer service process. In Figure 7, the initial model of the system is presented, showing the in-store service process of the SME prior to the proposed improvements. This highlights the reasons for the company's low OTIF levels: stockouts of supplies such as milk and tapioca and long service times caused by two main factors: the need to buy milk when it runs out and poor organization in the workspace. On the other hand, Figure 8 shows the model with the implementation of the proposed improvement. In this model, an auxiliary network for milk purchasing is added based on forecasted demand, with the expectation that there will be no unplanned purchases. Additionally, the input of tapioca and milk incorporates the distribution derived from demand forecasting.

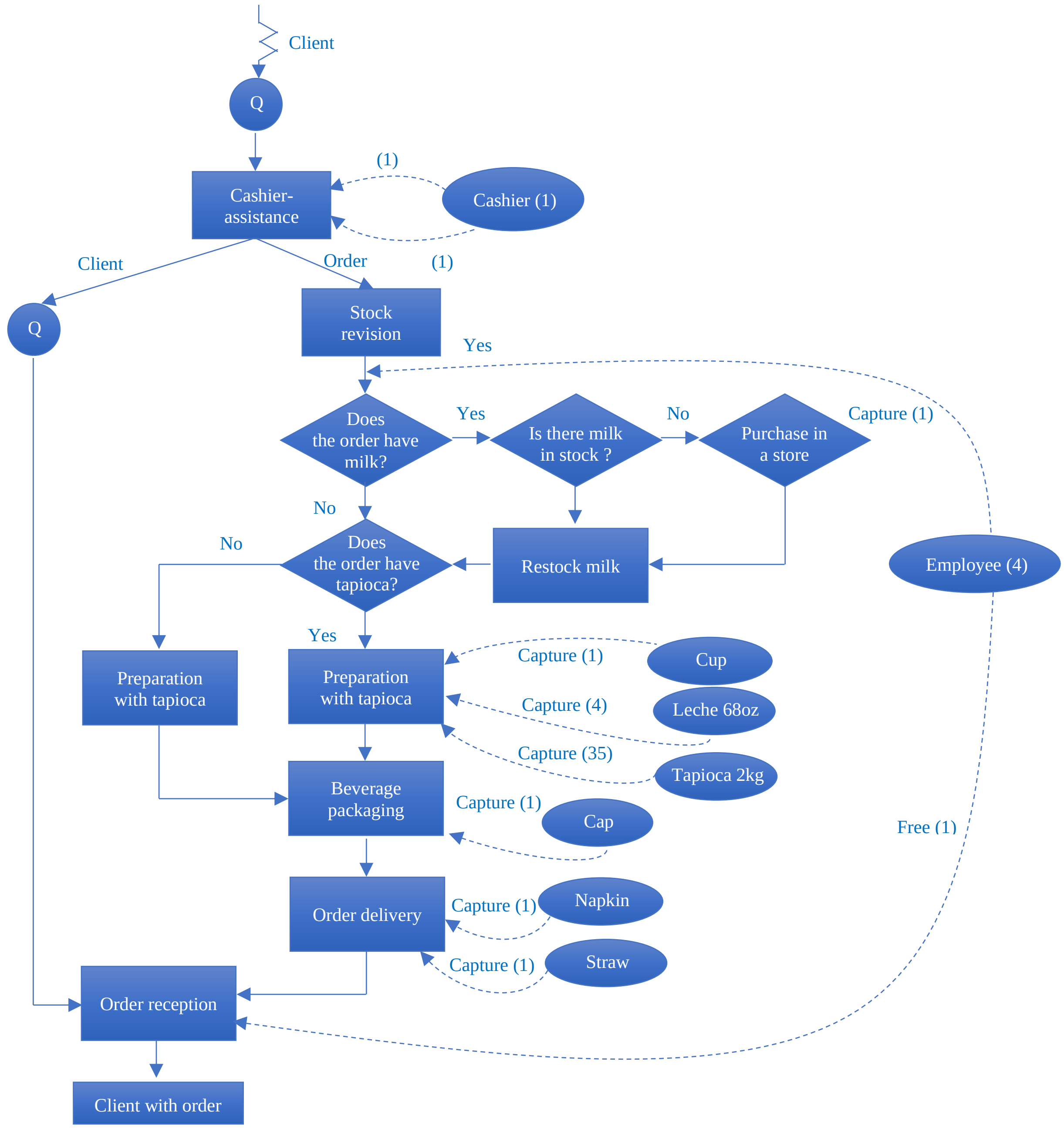

Fig. 6 Initial process diagram

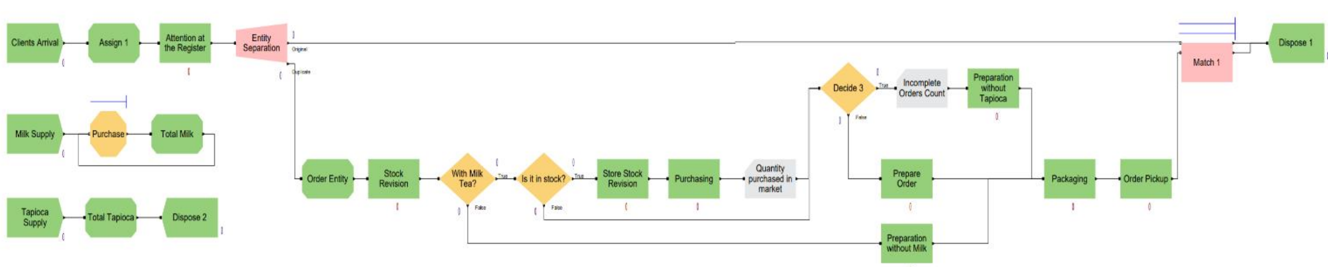

Fig. 7 Initial model in arena

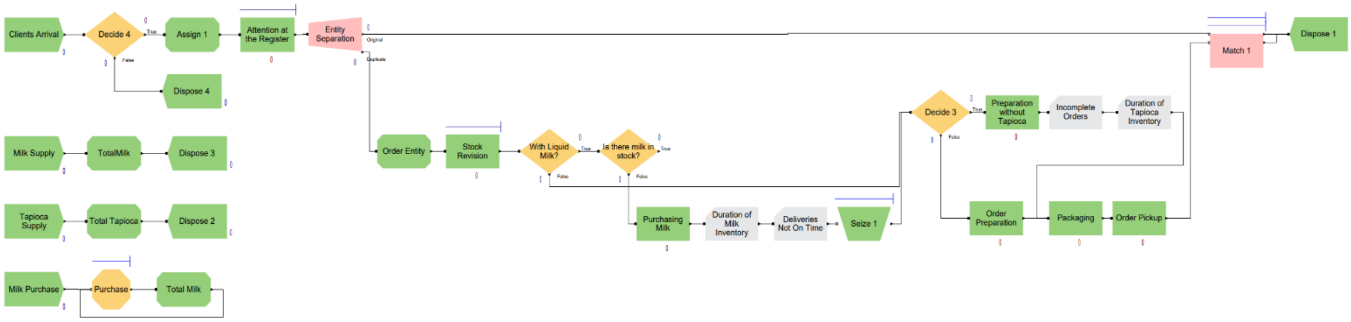

Fig. 8 Improved model in arena

4.3.3. Pilot Plan for Demand Forecasting with Machine Learning

For demand forecasting, various methods were evaluated using software such as Minitab and Orange to estimate the one with the lowest Mean Absolute Percentage Error (MAPE), an indicator used to assess a model's forecasting error. This analysis includes linear, quadratic, and exponential regression, moving average, simple exponential smoothing, Holt's method, and ARIMA to determine the error for each, as shown in Figures 9 and 10.

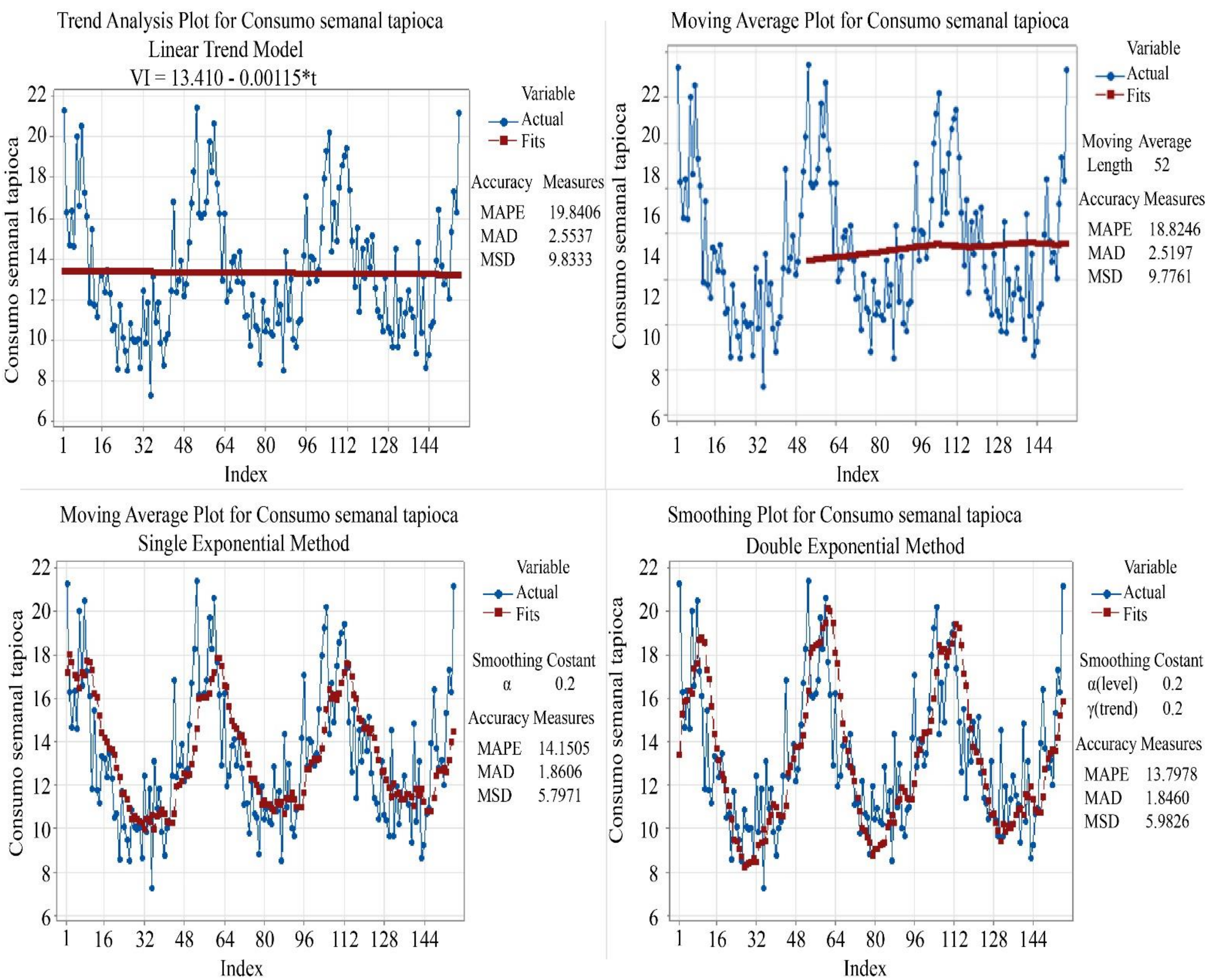

Fig. 9 Weekly tapioca consumption forecast

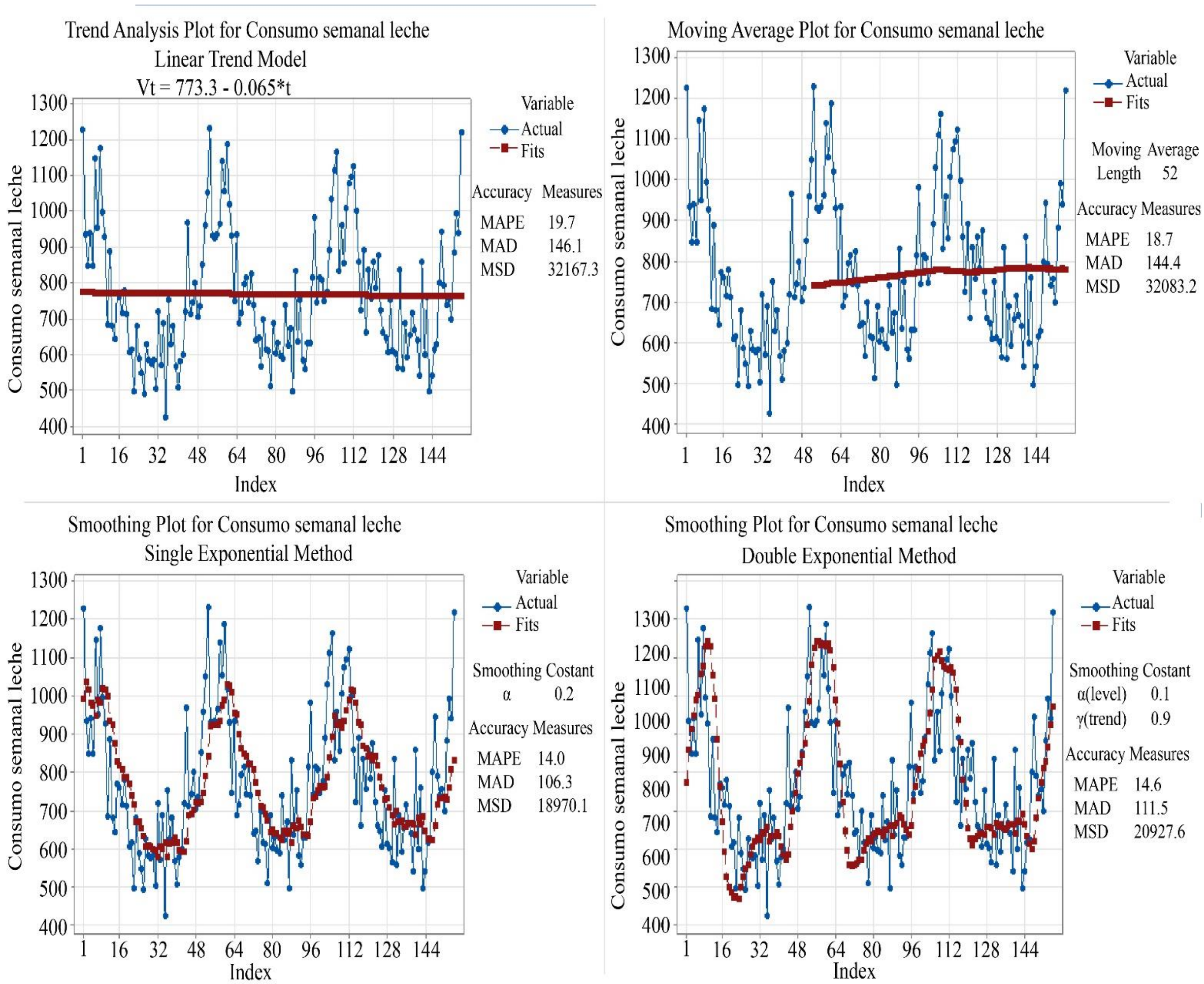

Fig. 10 Daily milk consumption forecast

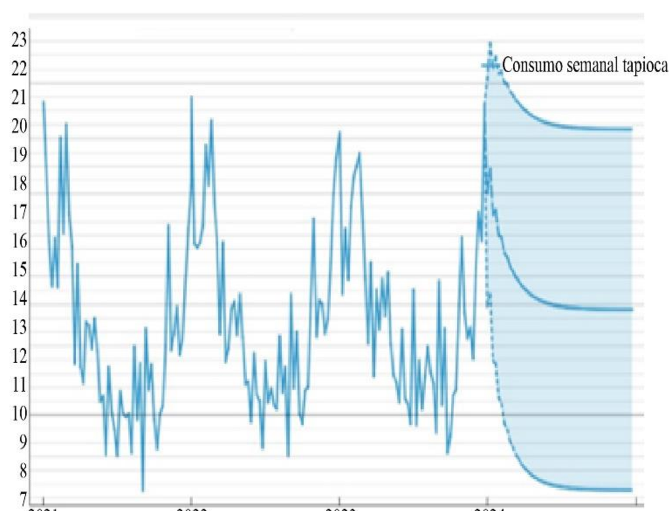

Fig. 11 ARIMA model for weekly tapioca forecast

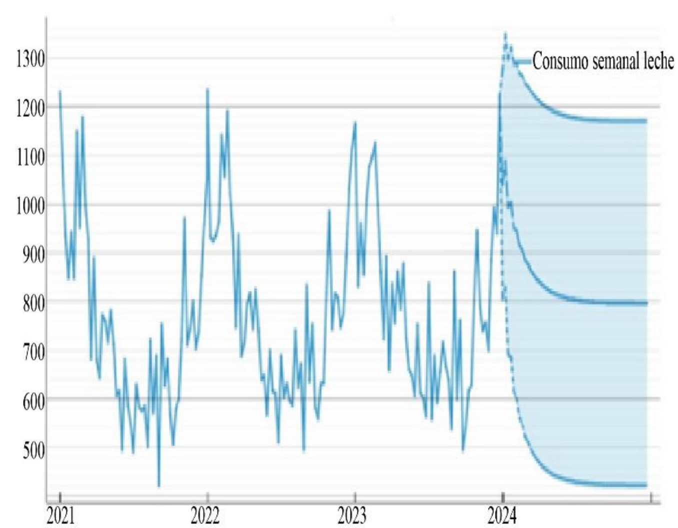

Fig. 12 ARIMA model for weekly milk forecast

The ARIMA model was developed using Orange software, a platform written in Python that is known for its graphical interface for data analysis. The ARIMA model in Orange allows for analyzing the different results that appear when changing the autoregression, differencing, and moving average variables (p, d, q). In the weekly tapioca forecast, ARIMA(2,0,1) produced the lowest errors, with a MAPE of 13.2%, as shown in Figure 11. On the other hand, the variables that showed the lowest errors in the milk consumption forecast had a p-value of 0. As a result, the evaluated model was ARIMA(2,0,1), which yielded a MAPE of 13.1%, as seen in Figure 12. Based on the developed forecasts, it can be concluded that the ARIMA method has the lowest MAPE, as it predicts seasonality with greater dynamism, achieving a MAPE of 13.10% and 13.20% for weekly tapioca and milk consumption, respectively. Table 5 below presents a comparison of percentage errors across the evaluated methods.

Table 5. MAPE regarding forecasting methods evaluation

Forecasting method	**Tapioca Consumption Forecast MAPE**	**Milk Consumption Forecast MAPE**
Linear regression	19.84%	19.70%
Quadratic regression	19.78%	19.60%
Exponential regression	18.97%	18.80%
Moving average	18.82%	18.70%
Simple exponential smoothing	14.15%	14.00%
Holt method	13.80%	14.60%
ARIMA	13.10%	13.20%

Table 6. Distribution table

Concept	**Distribution**
Weekly milk consumption	796 + WEIB(22.1, 0.527)
Daily tapioca consumption	2.03 + 2.17 * BETA(0.713, 1.04)

With the forecasts obtained from ARIMA, considering a 95% confidence interval, the distributions can be calculated by inserting them into the input analyzer. For weekly milk provisioning, the distribution remains consistent; however, the forecasted weekly tapioca quantity must be updated weekly so that new data can feed back into the model, which is applied through Machine Learning. Table 6 presents the distributions that follow the input forecasts, allowing these data to be inserted into the simulation to validate the effectiveness of the tool. With the report obtained from the final simulation carried out in the arena software, it was possible to get the different data of weekly and daily use respectively of the milk and tapioca inputs; based on this, the distributions could be found, which are found in Figures 13 and 14, to make the respective graphs and find the data necessary to calculate the indicators.

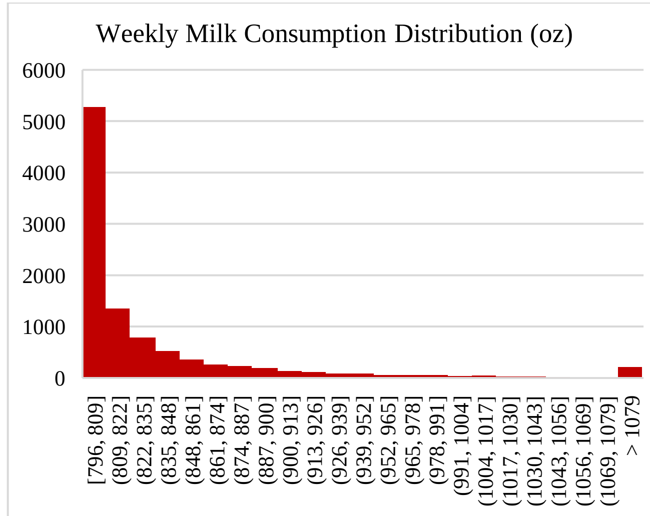

Fig. 13 ARIMA model for weekly milk forecast

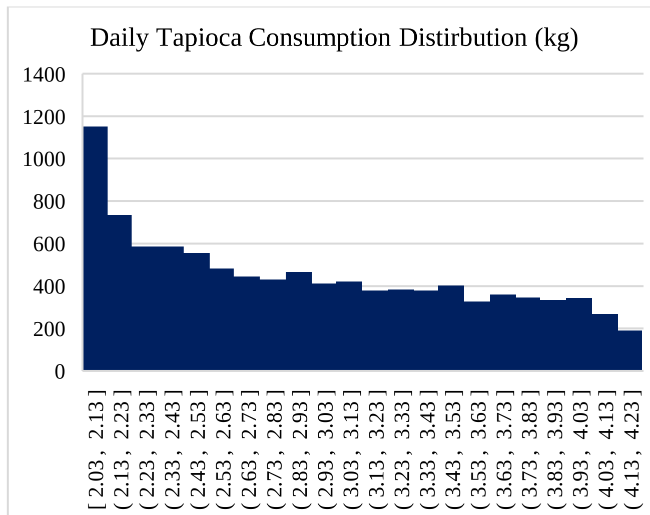

Fig. 14 ARIMA model for daily tapioca distribution

4.3.4. Results

Table 7 presents the results of the implementation of the improvement tools. As could be seen previously, the initial process was very inefficient. Many cycle times lasted longer than necessary due to purchasing the missing input at the time. Using the model to avoid having stock shortages can produce significant achievements.

Machine Learning addresses specific service problems, such as reducing cycle times and eliminating stockouts. Machine Learning allowed dynamic adjustments to the demand forecast with new data, which lowers the variability of demand in this sector. 5S created a disciplined and organized environment by actively involving workers, which helped organize work and storage areas, which reduced search times for supplies and order preparation errors, which had not been done before. In this sector, customer-product interaction is important.

Table 7. Results of model implementation

Issue	As Is	To Be	Improved	Cause	Indicator	As Is	To Be	Improved
Low OTIF	20.29%	92%	99.87%	Lack of process optimization	Total order cycle	8.16 min	5 min	1.96 min
				Insufficient supply planning	Forecasting error	Tapioca: 26.72% Milk: 45.71%	7%	Tapioca: 13.2% Milk: 13.1%
				Inadequate inventory management	Stock duration	Tapioca: 0.21 days Milk: 1.33 days	Tapioca: 1 day Milk: 7 days	Tapioca: 0.28 days Milk: 7 days

Table 8. Economic ratios

Ratio	Result
COK	14.97%
NVP E	S/. 42 955.51
IRR E	224.97%
B/C E	10.37
Payback Period	15 days

Previous studies have evidenced that these tools were not implemented combined in the service sector, unlike the manufacturing sector. Even so, better results could be achieved, as using this model enabled the simultaneous addressing of both operational and strategic problems. The innovative model managed to improve forecasting errors and optimize the layout. Therefore, the customer experience was refined, along with the company's competitiveness. In addition, the Arena software offered a quantitative validation of the model's impact, which offers the certainty of having significant, measurable and optimal improvements.

4.3.5. Economic Validation

Based on various databases and calculations, a risk-free rate of 4.66%, a leveraged beta of 1.44, a risk premium of 6.10%, and a country risk of 1.54% were obtained. These figures result in a cost of capital (COK) of 14.97%.

As shown in Table 8, the improvement project is viable without the need for financing. The Economic NPV of S/ 42,955.51, being greater than 0, indicates a positive return on investment. This is confirmed by the Economic IRR of 224.94%, which is higher than the COK of 14.97%, representing the minimum rate of return required by investors to justify the risk of investment. The COK demonstrates that the return on investment exceeds the minimum required by investors. Additionally, the Benefit/Cost ratio confirms that the investment generates a positive benefit. The payback period of 15 days indicates a quick recovery of the investment thanks to the improvements implemented.

5. Discussion

5.1. New Scenarios

The company studied has another product line: Fruit Tea and Slush, which represent 30% of the demand. These beverages have the same service times as the previously analyzed line, Milk Tea and Smoothie; however, they differ in preparation time and stock review. This is because these products do not use milk as an ingredient, so the implementation of 5S to reduce times and demand forecasting for the daily preparation of the main ingredient, namely tapioca, would be analyzed.

Table 9. Results table of the model application in new scenarios

Indicator	Current value	Results obtained in the improvement	Results
Forecast error	39.56%	7%	10%
Inventory Duration	0.18	1	0.34
Total order cycle	4.72	5	1.13
OTIF	30.62%	92%	50.33%

As observed in Table 9, the application of the 5S methodology also reduced the total cycle time, thereby increasing the on-time order rate. Regarding the application of Machine Learning, it was found that using demand forecasting data for preparation resulted in a higher rate of complete deliveries. Considering the rate of complete and on-time deliveries, the OTIF (On Time In Full) increased as a result. When comparing these results with those obtained from applying the model to the studied product line, an improvement in the proposed indicators was observed in both cases.

5.2. Analysis of Results

The total order cycle in the initial scenario was 8.16 minutes, which was aligned with the SME's pilot time tests. However, it exceeded the sector's standard of 5 minutes. This excess was caused mainly by stockouts, as employees had to spend time purchasing supplies from nearby stores instead of preparing beverages. These outlier times skewed the average upward, along with disorganization and inefficient layout routing, which were addressed through 5S. According to Saavedra and Zelada, 5S can reduce unnecessary movements by 60%, significantly improving cycle times. [19] As shown in Table 6, addressing these issues reduced cycle times, enabling the SME to compete with large chains' service times.

On the other hand, the improvements in forecasting error were significant despite not reaching the ideal scenario. The error in forecasting prior to implementing the Machine Learning model was 26.72% for tapioca and 45.71% for milk, leading to perceived product shortages and customer dissatisfaction. A lack of strategic supply planning caused these high errors, as the stocked supply remained constant despite fluctuations and stockouts. Nevertheless, by estimating demand using a model able to learn from historical data, the error was reduced to 13.10% and 13.20% for tapioca and milk. This 50% error reduction aligns with other studies, attesting to the success of this tool. [20] Although the stock duration results did not achieve the expected levels, the tapioca duration improved by 7%, an adequate increase considering the high variability in forecasting sales in days. On the contrary, the milk duration improved from 1.33 days to 7 days, succeeding in erasing milk stockouts and, in consequence, reducing cycle times significantly.

As a result of these components, the On Time and In Full Rate decreased by 79.58%, surpassing the sector's standards. This increase was mainly influenced by the Fill Rate indication, which consisted of delivering complete products. The Fill Rate depended on adequate stock duration, and forecasting helped leverage positive outcomes. Subsequently, zero milk stockouts boosted the On Time indicator, as outliers were erased, and 5S optimized the layout in order to reduce time lost in searching for materials. However, it is important to consider that the SME's initial OTIF rate was substandard due to problems in methodology, process, and structure. These issues were resolved with both analytical and process-oriented tools, as employees needed the technical knowledge to estimate adequate supply and the order, cleanliness, and discipline required to optimize the process and leverage positive results.

Additionally, the effectiveness of the proposed model can be verified by its application in new scenarios with different production lines, such as Fruit Tea and Slush. Despite not using the same ingredients, issues of tapioca stockouts and low OTIF persist, along with the positive impact of the model, which led to a 19.71% increase in OTIF.

5.3. Future Work

The scope of using the model comprising 5S and Machine Learning lies in expanding existing scientific boundaries. These tools lead to continued contributions to the improvement of supply planning, both for procurement and daily preparation, as well as the reduction of preparation and supply search times. The following outlines the potential future work regarding this field:

- Investigate and explore additional Lean techniques that may be applicable in the service sector.
- Research and combine Lean techniques with demand forecasting tools that can be applied to both manufacturing and service sectors and demonstrate the advantages of using them together.
- Conduct research using the application of the studied model and analyze its long-term impact.
- Utilize Machine Learning not only in procurement and preparation but also to understand customer preferences and, based on that, improve service quality and, consequently, customer satisfaction.
- Apply the proposed model to address other latent issues in the sector, such as reducing waste due to poor supply planning.

6. Conclusion

This research emphasizes the importance of adopting an innovative model in the food and beverage service sector to increase customer satisfaction and enhance the company's competitiveness. The study identified the key challenge for the SME under review is the low rate of OTIF orders. The impact of this problem is reflected throughout the literature, caused by errors in order planning, inadequate inventory management, and inefficient processes. The analysis of these factors led to the identification of root causes for low OTIF: long total order cycle time, high forecast error, short inventory duration, low number of complete deliveries, and low number of on-time deliveries.

The findings revealed a 51.62% increase in OTIF orders, alongside improvements in total order cycle time (75.98%), forecast error (46.13%), and inventory duration (8.14%). These results underscore the importance of leveraging innovative tools to enhance not only customer satisfaction but also the company's competitiveness, reducing the gap between the SME's performance and industry standards.With this research, possible future research directions can be developed, such as the use of additional Lean techniques in the sector. Future work may combine these tools to apply them to the service and manufacturing sector, which would present results regarding the effectiveness in the long term. Additionally, Machine Learning could be implemented further to learn from customer preferences. Furthermore, the proposed model addresses a research gap in the literature: the improvement of OTIF in the food and beverage service sector. This project also seeks to demonstrate the impact of Machine Learning and 5S tools in enhancing both customer satisfaction and cost efficiency, making it important to explore the potential benefits of this model across various sectors facing similar challenges.

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