

Stock Management in Automated Pharmaceutical Warehouses: Improved Detection and Replenishment

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Abstract

The sustained growth of the pharmaceutical industry, combined with the increasing complexity of supply chains, has intensified the demand for more efficient, reliable and technologically integrated logistics solutions. With increasing demands for traceability, safety and speed in the distribution of healthcare products, there is a need to think carefully about storage and order preparation systems, especially in contexts with high turnover, such as automated logistics centres.

In this context, A-Frame dispensers, widely adopted for the automatic picking of high-turnover items, depend critically on the efficiency of replenishment processes to maintain optimum performance levels. Carrying out this process manually, without digital support and systematic prioritisation criteria, leads to vulnerabilities with a direct impact on the system's operational reliability and efficiency.

This dissertation was carried out at Medlog, a company belonging to the Cooprofar group, with the objective of analysing the refuelling process of A-Frame systems in a real-life context. The goal was to identify operational limitations and propose solutions geared towards greater control, automation and efficiency. The project began with a diagnosis of operations, based on direct observation, analysis of historical data, interviews with operators and ergonomic assessment of workstations. The results of this diagnosis revealed a frequency of logistical failures, attributed to the absence of product in the channels when orders were being prepared, a phenomenon associated with exclusive dependence on the operators' visual perception.

Given this scenario, three proposals were designed and analysed, differing in terms of technological complexity. The first proposal involves the installation of automatic vertical modules for storage and replenishment, allowing physical and digital integration with the warehouse management system. The second is based on the development of a predictive model, supported by automatic learning algorithms, capable of anticipating replenishment needs based on historical consumption patterns. The third proposes the application of industrial cameras equipped with computer vision technology, capable of autonomously detecting the level of stock in each channel. The solutions designed were validated in a simulated environment using a discrete event model implemented in Python using the SimPy library.

The results obtained show improvements in terms of system reliability, reduced response times and improved working conditions. It was found that the success of the implementation depends on the compatibility between the technological solution adopted and the physical and organisational reality of the company. The comparative analysis of the solutions showed that although the alternative based on automated storage provides the best overall performance, the predictive model represents a balanced intermediate solution, combining moderate investment with positive operational impacts and ease of implementation. In turn, the solution based on computer vision showed high potential, but with more demanding technical and financial requirements.

Resumo

O crescimento sustentado da indústria farmacêutica, aliado à crescente complexidade das cadeias de abastecimento, tem vindo a intensificar a procura por soluções logísticas mais eficientes, fiáveis e tecnologicamente integradas. Com o aumento das exigências relativas à rastreabilidade, segurança e rapidez na distribuição de produtos de saúde, impõe-se uma reflexão profunda sobre os sistemas de armazenagem e preparação de encomendas, especialmente em contextos de elevada rotatividade, como é o caso dos centros logísticos automatizados.

Neste enquadramento, os dispensadores *A-Frame*, amplamente adotados para o *picking* automático de artigos com elevada rotação, dependem, de forma crítica, da eficácia dos processos de reabastecimento para manterem níveis ótimos de desempenho. A realização manual deste processo, desprovida de apoio digital e de critérios sistemáticos de priorização, origina vulnerabilidades com impacto direto na fiabilidade e eficiência operacionais do sistema.

A presente dissertação foi desenvolvida na Medlog, empresa pertencente ao grupo Coopprofar, com o propósito de analisar o processo de reabastecimento dos sistemas *A-Frame* em contexto real. Procurou-se identificar limitações operacionais e propor soluções orientadas para um maior controlo, automatização e eficiência. O projeto teve início com um diagnóstico das operações, sustentado na observação direta, análise de dados históricos, entrevistas aos operadores e avaliação ergonómica dos postos de trabalho. Os resultados deste diagnóstico revelaram frequência de falhas logísticas, atribuídas à ausência de produto nos canais no momento da preparação das encomendas, fenómeno associado à dependência exclusiva da perceção visual dos operadores.

Perante este cenário, foram concebidas e analisadas três propostas, diferenciadas em termos de complexidade tecnológica. A primeira proposta envolve a instalação de módulos verticais automáticos para armazenagem e reposição, permitindo a integração física e digital com o sistema de gestão de armazém. A segunda baseia-se no desenvolvimento de um modelo preditivo, sustentado por algoritmos de aprendizagem automática, com capacidade para antecipar necessidades de reabastecimento com base em padrões históricos de consumo. A terceira propõe a aplicação de câmaras industriais dotadas de tecnologia de visão computacional, capazes de detetar autonomamente o nível de *stock* em cada canal. As soluções concebidas foram validadas em ambiente simulado, recorrendo a um modelo de eventos discretos implementado em *Python* com recurso à biblioteca *SimPy*.

Os resultados obtidos demonstram melhorias ao nível da fiabilidade do sistema, da redução do tempo de resposta e da melhoria das condições de trabalho. Verificou-se que o sucesso da implementação depende da compatibilidade entre a solução tecnológica adotada e a realidade física e organizacional da empresa. A análise comparativa das soluções evidenciou que, embora a alternativa baseada em armazenamento automatizado proporcione o melhor desempenho global, o modelo preditivo representa uma solução intermédia equilibrada, conjugando investimento moderado com impactos operacionais positivos e facilidade de implementação. Por sua vez, a solução baseada em visão computacional revelou potencial elevado, mas com requisitos técnicos e financeiros mais exigentes.

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"La connaissance est une forme de liberté"

Simone de Beauvoir

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Acronyms and Symbols

AI	Artificial Intelligence
A-Frame	Automatic Picking Frame
BI	Business Intelligence
CAGR	Compound Annual Growth Rate
CV	Coefficient of Variation
DAX	Data Analysis Expressions
d^+ / d^-	Positive / Negative Deviations
EOQ	Economic Order Quantity
ERP	Enterprise Resource Planning
ETL	Extract, Transform, Load
FEFO	First Expired, First Out
FIFO	First In, First Out
IoT	Internet of Things
KPI	Key Performance Indicator
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MCDM	Multi-Criteria Decision Making
MPS	Manual Picking Station
OSR	Order Storage and Retrieval System
PDT	Portable Data Terminal
REBA	Rapid Entire Body Assessment
RFID	Radio Frequency Identification
RMSE	Root Mean Square Error
ROI	Return on Investment
RULA	Rapid Upper Limb Assessment
SDA	Automated Dispensing System
SKU	Stock Keeping Unit
SQL	Structured Query Language
SS	Safety Stock
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TN	Total Number of Items
TP	Total Product Value
VLM	Vertical Lift Module
WMS	Warehouse Management System
XYZ	Demand Variability Classification

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Chapter 1

Introduction

This dissertation project presents the work carried out over five months at MedLog, S.A, a company belonging to the Cooprofar Group, recognised as one of the main pharmaceutical distribution operators in Portugal. The study arose from the perceived need to improve levels of automation and make logistics processes more efficient, which is important to guarantee a supply chain that operates in a stable and effective manner. In particular, special attention was paid to the storage and supply phases of the A-Frame dispenser channels, as these are critical stages with a direct impact on operating costs, the occurrence of errors and the quality of the service provided.

This chapter presents the background to the work, the reasons behind its development and its scope. The company is also briefly characterised, the main objectives of the project are defined, the stages that marked the course of the work are explained and, finally, the general structure of the dissertation is described.

1.1 Dynamics of the Pharmaceutical Sector and Operational Challenges

The pharmaceutical industry has seen significant global expansion in recent years. The most recent forecasts point to a market value of between 1.75 and 1.78 trillion dollars by 2026, representing a compound annual growth rate (CAGR) of between 3% and 6%. This evolution consolidates the industry's central role in responding to the new demands of healthcare systems, as well as incorporating technological innovations that have driven profound transformations in the sector (Research and Markets, 2025).

Several factors have contributed to this expansion, not least the increase in the prevalence of chronic diseases worldwide. This trend has accentuated the dependence on the research and development sector, accelerating the introduction of innovative medicines and therapies. At the same time, demographic changes, especially the ageing of the population, have led governments in various countries to increase investment in health, in an attempt to meet the growing demand for medical care (Chomać-Pierzecka, 2025).

The expansion of emerging markets allows this growth trajectory to be further amplified in developing economies, particularly China, Brazil and India, which are showing higher expansion rates between 5% and 11%. At the same time, global efforts to improve pharmaceutical accessibility, combined with increased competition in the market for biosimilars and generic alternatives, are fundamentally transforming the dynamics of the industry (Islam and Hossen, 2025).

This global market expansion has directly impacted Coopprofar's operations, manifesting in three key developments: a growing client base, increased order volumes, and greater product inflows from suppliers. While indicative of business success, this growth has progressively strained warehouse capacity, creating operational bottlenecks that underscore the urgent need for process optimization and efficiency enhancements throughout the supply chain.

Presently, Coopprofar's operations still rely significantly on manual processes conducted by operators, as several key tasks remain unautomated. These labor-intensive procedures exhibit inherent vulnerabilities to human error, resulting in operational delays, uneven workload distribution, and ultimately diminished service quality for client companies. This context necessitates a comprehensive analysis of existing manual workflows, an evaluation of error-related operational impacts, and an exploration of available automation solutions. Crucially, any proposed interventions must undergo rigorous cost-benefit analysis, carefully balancing process efficiency with financial viability to ensure sustainable improvements.

1.2 Coopprofar - *Cooperativa dos Proprietários de Farmácia, CRL*.

The Coopprofar Group - *Cooperativa dos Proprietários de Farmácia, CRL* - is the leading pharmaceutical distribution co-operative in Portugal, with over fifty years' experience in the sector since it was founded in 1975. With a network encompassing more than 1,400 affiliated pharmacies, the organization serves as a critical nexus in Portugal's medicine and healthcare product distribution ecosystem. As the largest pharmaceutical group with exclusively national capital, Coopprofar holds a dominant position in the market, attested to by its annual turnover of approximately 390 million euros and its recognition as one of the most competitive entities in the sector (Coopprofar, 2024).

The group integrates several subsidiary companies, each performing specialized functions within the organizational hierarchy. As illustrated in Figure 1.1, these entities maintain distinct operational roles while contributing synergistically to the collective organizational structure.

Medlog - *Investimentos e Participações, SGPS, SA.*, created in 2008, is the entity responsible for the strategic management of the group's activities, ensuring the centralisation of shareholdings in the various companies that make up the group.

The project described was carried out at Medlog - *Logística Farmacêutica, SA.*, the company responsible for the logistics management of the group's warehouses, as well as providing personalised distribution solutions for the pharmaceutical industry and hospital units.

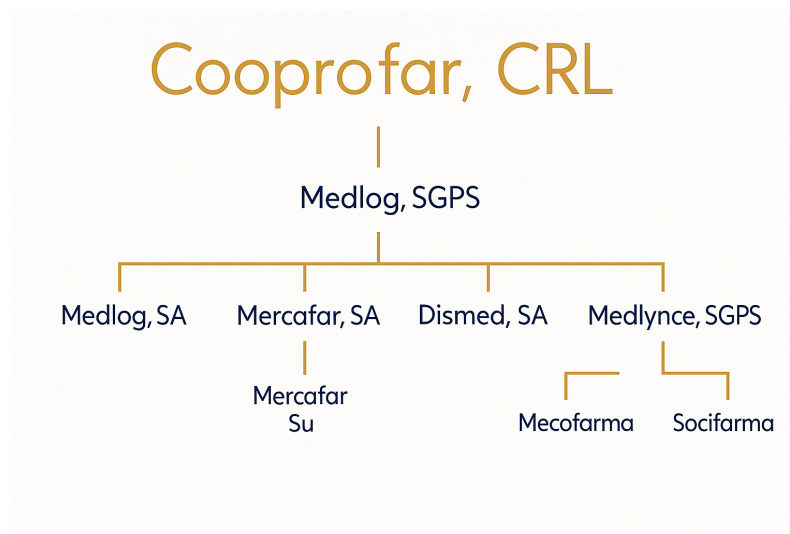


Figure 1.1: Organizational chart (Cooprofar, 2024)

Mercafar - *Distribuição Farmacêutica, SA*. has been operating since 1999 in the representation, promotion and distribution of health products, targeting pharmacies, drugstores, hospitals, health centres and other establishments in the sector. In addition to the domestic market, the company has expanded its activity into international trade, having started selling and exporting to various markets in 2010.

Dismed - *Transporte de Mercadorias, SA.*, in turn, specialises in the transport of healthcare products in Portugal, with strict environmental control and continuous monitoring of operations, ensuring a flexible service in line with the best distribution practices.

The Cooprofar-Medlog Group, in which the project was developed, operates five logistics platforms in different locations. The largest warehouse, with an area of 11,000 m², is located in Gondomar and was the main location for the project. With the aim of ensuring greater proximity to its customers throughout Portugal, the group also has warehouses in Macedo de Cavaleiros (1,040 m²), Aveiro (1,000 m²) and Alcochete (4,000 m²), totalling a storage area of 17,040 m². The Figure A.1 in Appendix A shows the exact location of these facilities, demonstrating an effective distribution strategy that ensures efficient national coverage.

1.3 Objectives of the project

The aim of this project is to critically analyse and compare the technological solutions available on the market for implementing an automated system for monitoring stock levels organized by channel (where each channel corresponds to a specific type of product). This included a thorough analysis of the A-Frame system itself, its functioning, internal organisation, and operational data, in order to identify bottlenecks and evaluate potential areas for improvement. This system should enable not only the automatic detection of inventory levels, but also the autonomous generation of replenishment orders and their intelligent prioritisation.

Currently, the replenishment process in the A-Frame system is based on a visual check that follows the principles of the Kanban methodology, an approach that is limited in the face of today's demands for logistical efficiency. In order to overcome these limitations and achieve the proposed objectives, the project was structured into several fundamental stages of analysis.

Firstly, a survey of the current context (As-is) was carried out in collaboration with the operational team, taking into account the rules and requirements of stock management, including the FEFO (First Expired, First Out) principle, product positioning strategies, batch change and expiry control, and replenishment priorities. This was followed by an operational and organisational analysis of the A-Frame system itself, assessing its internal configuration, functioning, and processing capacity, with the support of data analysis to identify bottlenecks and potential improvements.

The next step involved identifying the available market solutions for the automatic detection of stock levels within A-Frame channels. These solutions were then analysed and compared, considering their respective advantages and disadvantages, with the goal of selecting the most advantageous one for implementation. An estimate of the required investment for the chosen solution was also made, along with an analysis of the operational impact of its adoption. This included the identification of new working conditions to be considered, employee satisfaction levels, the quality of service as reflected in a reduction of stock replenishment complaints, and the expected variation in operating costs.

Finally, the impact of the proposed process change was evaluated in terms of its effect on the Key Performance Indicators (KPIs) of the internal logistics team.

1.4 Methodology

The main purpose of this project is to study and analyse the current process of filling the channels of the A-Frame system, with a view to developing a solution that will make it possible to automate and control this activity, eliminating existing downtime and helping to reduce operating costs and increase the efficiency of the operation. In order to overcome these limitations and achieve the proposed objectives, the project has been structured into several fundamental stages of analysis.

The work was carried out over the course of an eighteen-week internship, structured around five main phases: integration, preparation, development, analysis and finalisation. Each stage involved specific tasks, defined according to the objectives set for each stage of the project. The time distribution of these activities is shown in Figure 1.2.

The first four weeks allowed us to establish contact with the company's teams and internal processes, facilitating direct observation of logistics operations. This initial phase was necessary to understand the existing dynamics and identify the main limitations associated with the current channel supply system.

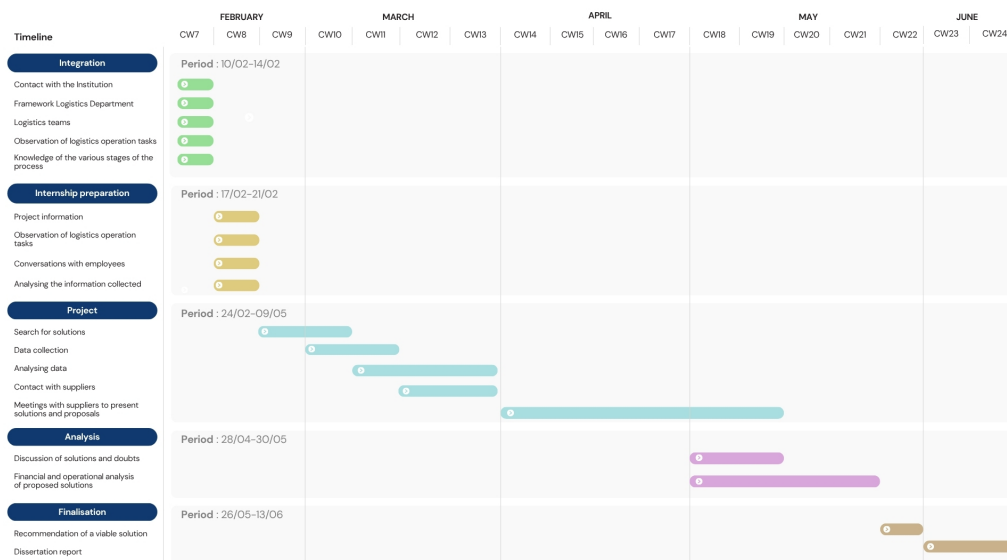


Figure 1.2: Internship plan timetable

From the fifth week onwards, the structured development of the project began, running until week fourteen. This period corresponded to the application of the methodology defined for the study, divided into four sequential phases, presented in Figure 1.3. Each phase contributed to a systematic progression from diagnosing the current situation to the quantitative evaluation of concrete solutions.

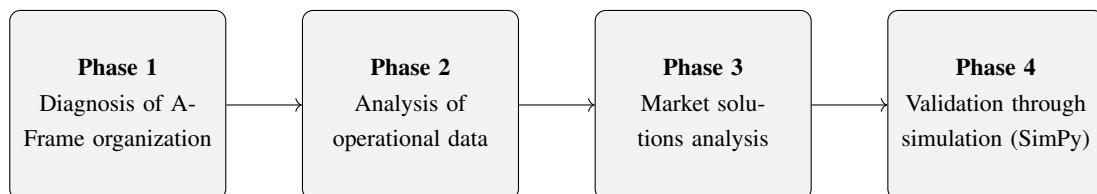


Figure 1.3: Methodological structure adopted in the project

The first phase, corresponding to weeks 5 and 6, consisted of a detailed analysis of the operation of the A-Frame system. Aspects such as the physical distribution of the channels, the way products are allocated and the frequency of operational deviations associated with supply were assessed. This analysis was important for identifying weaknesses and opportunities for improvement.

In the second phase (weeks 7 and 8), operational data was processed and analysed, based on information collected from the company's management system (ERP). This stage made it possible to quantify the problem, assess its impact on logistics performance indicators and provide technical support for future decisions.

The third phase, between weeks 9 and 11, focussed on identifying technological solutions with application potential. Various alternatives available on the market were analysed, contacts were made with suppliers and information was gathered on the costs, implementation requirements and limitations of each proposal.

Finally, the fourth phase, corresponding to weeks 12 to 14, consisted of creating and applying a simulation model developed using the SimPy library. This simulation made it possible to test the performance of each solution in a virtual environment, comparing the results based on operational and financial criteria. This approach enabled an objective assessment of the proposed alternatives, allowing the final decision to be based on concrete data.

The final weeks of the internship (15 to 18) were dedicated to choosing the most suitable solution, writing this dissertation and formally presenting the project to the company.

1.5 Dissertation structure

This dissertation is organised into seven chapters, which present all the phases of the project in a clear and structured way, from the initial framework to the final conclusions.

The second chapter reviews the literature, covering the main concepts related to stock management and automated storage systems. Technological solutions relevant to the pharmaceutical sector are also analysed, as are the logistical factors that condition decision-making in complex operational contexts.

Chapter three describes the context of the company and its operations, with special emphasis on logistics processes. The limitations of the current system are identified, particularly with regard to the manual supply of A-Frame channels, which justifies the need for intervention.

The fourth chapter of the thesis is dedicated to analysing operational data. Based on the information extracted from the internal systems, the deviations recorded, the organisation of the products and the impacts observed on the efficiency of the logistics processes were studied.

Chapter five presents the technological solutions proposed and evaluates their impact from an operational, financial and strategic perspective. It includes both the description of each solution and the results obtained through discrete-event simulation. The analysis covers key performance indicators (KPIs), efficiency and reliability metrics, as well as a financial assessment and a strategic comparison based on a balanced scorecard approach. This integrated chapter allows for a complete view of the alternatives and supports the selection of the most suitable option.

Finally, chapter six brings together the main conclusions of the project, as well as suggestions for future work and reflections on the expected benefits of the recommended solution.

Chapter 2

Literature Review

The aim of this chapter is to provide a theoretical framework for this work by reviewing the literature on the main topics under study. Given the current demands in the logistics sector, and particularly in the pharmaceutical industry, it is essential to understand how inventory management functions and how warehouses are organized, as efficiency and responsiveness are critical success factors today. To establish this foundation, key concepts related to inventory management were first explored, including stock control models, replenishment policies, and the organizational structures of warehouses and distribution centers. This analysis makes it possible to identify the most common methods and realise where there are still limitations that affect logistics performance.

Then there was a reflection on ergonomics in logistics operations. Although it is often overlooked, this area is very important, especially in manual and repetitive tasks such as replenishing A-Frame channels, where the physical effort and posture of the operators are aspects to be taken into account. The third part focuses on automating inventory management, with an emphasis on A-Frame dispensers, stock monitoring and control technologies, and the latest trends in automation applied to logistics centres.

Finally, technological solutions applied to stock management are explored, including automated systems, sensors, computer vision and artificial intelligence. This review makes it possible to identify not only the state of the art, but also points that are still underdeveloped, helping to support the proposals for improvement presented in this work.

2.1 Inventory Management in Logistics

Christopher (1993) defines logistics as the business function responsible for efficiently managing the flow of goods, services and information along the supply chain, from origin to the point of consumption. Its main elements - transportation, inventory management, and storage - play a crucial role in the economy and industry, ensuring efficient movement of goods and services, reducing costs, and responding to customer demands (Lummus et al., 2001).

Inventory management is a central activity in the planning and operation of the logistics system (Ghiani et al., 2004). For a long time, this function was essentially focused on stock control, ensuring a stable supply of products. However, from the 80's, Japanese companies demonstrated that it was possible to operate with significantly lower stock levels, allowing capital previously invested in inventory to be directed to other strategic areas. In addition, factors such as delivery times, production times and quality costs were found to play a decisive role in operational efficiency (Möllering, 2007). Inventory management has thus evolved to encompass not only stock control, but also continuous improvement initiatives related to optimising warehouse layout, quality management and waste reduction (Richards, 2011).

2.1.1 Operating warehouse

Warehouses are facilities for storing and organising inventories and can be classified as production warehouses or distribution centres (DCs) (Staudt et al., 2015).

In DCs, products follow a well-defined operational flow (Figure 2.1). The process begins with receiving the products, which involves physically unloading the incoming shipments, checking purchase orders and registering the goods received in the computer system. This is followed by the storage phase, where the products are organised and placed in specific locations to optimise their management. When an order is received, the sorting of orders begins, ensuring that the correct products are collected and prepared for dispatch. The orders are then grouped together, value-added services are applied and the products are packaged. Finally, dispatch takes place, where the products are prepared for distribution (Rushton et al., 2010).

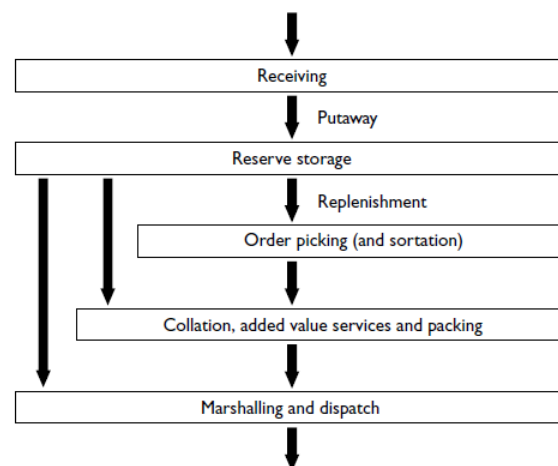


Figure 2.1: Typical warehouse flow (Rushton et al., 2010)

The structure of the warehouse and its operations depend on a number of characteristics, such as the physical properties of the products, the special storage conditions, the number of products stored and the volume of goods moved in and out of the warehouse (Ghiani et al., 2004). Therefore the organisation of a distribution centre is made up of different functional areas. The first is the reception area, where orders are received, unloaded and checked. This is followed by the storage

area, where the Stock Keeping Units (SKUs) are organised and stored. Finally, there is one or more dispatch zones, where orders are prepared and outbound vehicles are loaded. The transfer of SKUs from the reserve zone to the forward zone is called replenishment (Muller, 2019).

The common costs of a warehouse are defined and their respective proportions are shown in Figure B.1 in Appendix B. However, these costs can vary depending on the storage medium, the type of products and the organisation of orders. In addition, many of these tasks are difficult to automate, making them labour-intensive processes (Muller, 2019).

2.1.2 Stock Management Models

Stock management models are important tools for ensuring a balance between product availability and operational efficiency. By defining rules for storing, moving and replenishing materials, these models help to organise logistics flows, reduce waste and optimise resources. The choice of the most appropriate model depends on the characteristics of the products, the objectives of the operation and the control and traceability requirements.

FIFO, FEFO Stock management in pharmaceutical logistics is generally based on different methods, including First In, First Out (FIFO) and First Expired, First Out (FEFO). These methods determine the order in which products are stored, collected and dispatched, guaranteeing efficient organisation and compliance with the sector's requirements.

The FIFO method is based on the principle that the first products to enter the warehouse should be the first to leave, ensuring continuous stock rotation and minimising the risk of obsolescence. The FEFO method prioritises the products with the closest expiry dates, allowing them to be dispatched before the rest, in order to avoid waste and guarantee compliance with safety standards (Sazvar et al., 2016).

The application of these methods is essential in the pharmaceutical industry, not only to comply with current regulations, but also to preserve the quality and efficacy of the products. To do this, items are organised chronologically or based on their expiry date, with the most recent stored behind the oldest, making it easier to collect products with shorter expiry dates (Rezeki et al., 2022).

Just-in-Time Just-In-Time (JIT) is a production system created in Japan by Toyota with the aim of eliminating waste and improving operational efficiency. According to Ohno and Bodek (2019), one of its creators, JIT is based on the idea of supplying each stage of the production process with only what is needed, in the exact quantity and at the right time, avoiding the accumulation of unnecessary inventories.

This system is closely linked to the concept of continuous flow, in which production responds directly to demand and not to forecasts, thus reducing the risk of overproduction or stock-outs. As Monden (2011) points out, when JIT is applied effectively, it makes it possible to eliminate warehouses and reduce operating costs, increasing the return on invested capital.

In addition, JIT is supported by a pull-type production system, where each process “pulls” the materials it needs from the previous one, unlike the traditional push-type system, based on centralized forecasts and orders. According to Tersine (1994), this model challenges conventional methods of materials management, promoting an approach focused on eliminating everything that doesn’t add value to the end product, such as handling, storage or overproduction.

Kanban Kanban method has its origins in visual workflow management and is one of the pillars of the Toyota System, playing a key role in the Just-in-Time model. This method makes it possible to increase company productivity while minimising waste (Sendil Kumar and Panneerselvam, 2007).

The word Kanban originates in Japan and means ‘signboard’. In a production context, it refers to a card that contains all the information needed for the production or assembly of a product at each stage, detailing its route to completion. These cards are used to control the flow of production and stock management, allowing for a high volume of production and better use of installed capacity, reducing production times and optimising work in progress (Rahman et al., 2013).

The fundamental principles of Kanban involve visualising the stages of the process, controlling the number of tasks being carried out simultaneously and identifying bottlenecks, guaranteeing an efficient workflow. It also involves defining clear policies for the entire team, as well as holding frequent meetings to continually evaluate and improve the system (Fuentes-del Burgo et al., 2024).

2.1.3 Stock Replenishment Policies

Replenishment policies represent a set of important inventory management practices, with the aim of maintaining product availability at the lowest possible cost. These policies establish rules to answer two central questions: when to order and how much to order. The success of these decisions lies in the balance between storage costs, ordering costs and the risk of stock-outs (Toomey, 2000).

The main types of policy include continuous review systems, where replenishment is triggered whenever the stock level reaches a previously defined order point (reorder point), and periodic review systems, where the review and eventual replenishment of stock occur at fixed time intervals (Ghani et al., 2004). In both cases, it is common to use safety stock, characterized as an additional margin to prevent supply failures, especially when there are uncertainties in demand or delivery times (Rushton et al., 2010).

These policies should be selected according to the type of product, the predictability of demand and the company’s logistics structure. Rushton et al. (2010) point out, coordination between different levels of the supply chain is essential to ensure that material flows are efficient and responsive, reducing waste.

Economic Order Quantity The Economic Order Quantity (EOQ) model is one of the oldest and most widely used quantitative tools in inventory management. First developed by Ford W. Harris in 1913, the model makes it possible to determine the optimum order quantity that minimizes the

total cost of inventory, balancing the costs of ordering and the costs of holding stock (Tersine, 1994). The classic EOQ formula is presented as follows:

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (2.1)$$

where:

- D represents the annual demand;
- S is the fixed cost per order;
- H is the holding cost per unit, per year.

This model assumes that demand is constant, that delivery times are fixed and that there are no stock shortages or quantity discounts. The simplicity of the model makes it useful in stable contexts but, as Alnahhal et al. (2024) point out, it becomes limited when applied to modern supply chains, which are marked by variability and uncertainty.

In light of this, several extensions of the EOQ model have been developed, addressing situations such as products with imperfect quality, short life cycles, perishability, capacity limitations or even environmental requirements - such as reducing CO₂ emissions associated with transportation and storage (Alnahhal et al., 2024). These adaptations are essential to bring inventory management more into line with contemporary challenges, where environmental and logistical factors are becoming more strategically relevant (Simchi-Levi et al., 2007).

Reorder Point The reorder point is the stock level that, once reached, automatically triggers a new order. It is calculated on the basis of expected demand during the lead time and may include a safety stock component. This mechanism makes it possible to anticipate replenishment before stock runs out, avoiding shortages and lost sales (Rushton et al., 2010). The standard expression for the reorder point is given by Equation 2.2.

$$ROP = d \times L + SS \quad (2.2)$$

where:

- d = average demand per unit of time;
- L = lead time;
- SS = safety stock.

Safety Stock Safety stock is a strategic reserve of inventory kept to absorb uncertainties in demand or delays in supply. Its purpose is to ensure that customer service levels are not affected by unforeseen variations, maintaining operational continuity. The size of the safety stock depends on the variability of demand, the delivery time and the desired level of service (Toomey, 2000). The greater the uncertainty, the greater the stock needed to maintain supply reliability. A commonly used formula to calculate safety stock, under variable demand and constant lead time, is shown in Equation 2.3.

$$SS = z \times \sigma_d \times \sqrt{L} \quad (2.3)$$

where:

- z = service level factor (number of standard deviations);
- σ_d = standard deviation of demand;
- L = lead time.

2.1.4 Warehouse and Distribution Management

Warehouse and distribution management plays an important role in the logistics chain, being responsible for the organisation of physical space, stock control and the efficient movement of materials to the point of consumption. By implementing appropriate methods of sorting, planning and supply, it is possible to improve operational performance, reduce waste and adapt resources to demand requirements.

ABC Analysis ABC analysis is a widely used inventory classification technique based on the Pareto Principle, formulated by Italian economist Vilfredo Pareto at the end of the 19th century. This principle, also known as the 80/20 rule, holds that a small proportion of the causes (approximately 20%) are responsible for a large proportion of the effects (around 80%). This logic has been adapted to the business context to identify the inventory items that have the greatest financial impact, allowing them to be prioritized in stock control and management (Chu et al., 2008; Ravinder and Misra, 2016). Traditionally, items are segmented into three categories: those in class A, which represent around 20% of items but correspond to 70% to 80% of the total value; those in class B, with intermediate importance; and those in class C, which correspond to the majority of items (around 50%) but a small fraction of the value (Liu et al., 2016; Wild, 2002)

This method allows organizations to focus their management resources on the most critical items, applying greater control to A items, moderate control to B items and minimal control to C items. Ravinder and Misra (2016) point out that this approach contributes significantly to operational efficiency, especially in environments with large volumes of inventory. However, traditional ABC analysis is based solely on the criterion of the annual value of consumption, which may be insufficient for more complex contexts in which other factors such as criticality, lead time or obsolescence also play a relevant role. With this in mind, alternative and more comprehensive approaches have emerged, namely multi-criteria classifications.

Hybrid ABC Analysis Given the limitations of traditional ABC analysis, especially with regard to the consideration of only one criterion, several authors have proposed multi-criteria models. Among the most promising approaches is the hybrid methodology developed by Kheybari et al. (2019), which combines different decision support techniques: Shannon's Entropy to calculate objective criteria weights, TOPSIS to evaluate and rank items based on their proximity to the ideal, and Goal Programming to ensure compliance with the Pareto principle. In this analysis, criteria

(such as unit cost, annual consumption, criticality factor and lead time) are weighted automatically, avoiding subjectivity.

The value of each item is then determined by TOPSIS, and finally the items are classified into A, B and C by means of goal programming, ensuring that the final proportions respect both the number of items and the economic value per class. This solution proved to be statistically robust and, in comparative simulations, showed greater adherence to the original principles of ABC analysis, with less deviation in the allocations of value and number of items per class (Kheybari et al., 2019).

This evolution of ABC analysis represents a practical response to the current demands of inventory management, allowing for a more realistic, flexible classification in line with companies' strategic objectives when there are multiple criteria under analysis.

ABC/XYZ analysis XYZ analysis is a complementary technique to ABC analysis, used in inventory management to classify items based on the variability of demand over time. While ABC classification focuses on the annual consumption value of items, XYZ analysis assesses the predictability of demand, making it possible to distinguish between items with stable, fluctuating or irregular demand. According to Scholz-Reiter et al. (2012), this analysis is crucial for adjusting material planning and replenishment strategies according to the consistency of historical consumption.

The classification is based on the coefficient of variation (CV), defined as the ratio between the standard deviation and the average demand over a given period. Based on this indicator, items are classified:

- X: low variability ($CV < 10\%$), with stable and predictable demand;
- Y: medium variability ($10\% \leq CV \leq 30\%$), with seasonal fluctuations or moderate trends;
- Z: high variability ($CV > 30\%$), with irregular or unpredictable demand (Zenkova et al., 2020).

The XYZ analysis is widely applied in combination with ABC analysis, forming the ABC/XYZ matrix, which segments items into nine groups. This matrix, shown in Appendix B, allows managers to adopt differentiated control policies, for example, AX items (high value, stable demand) require high priority and continuous supply, while CZ items (low value, unstable demand) can be managed more flexibly or even discontinued (Buliński et al., 2013).

2.2 Ergonomics in Logistics Operations

Ergonomics emerged as a response to the need to adapt work systems to the physical, cognitive and organisational characteristics of human beings (McCauley-Bush, 2011). As an applied discipline, it brings together knowledge from various fields such as physiology, psychology, design and engineering with the aim of creating working conditions that are simultaneously safe, efficient and comfortable (Dul and Weerdmeester, 2008).

The differentiation is that humans should normally adjust to the workstation, but ergonomics proposes precisely the opposite, that the system should be designed according to human capacities and limitations (Bridger, 2017). This holistic approach is particularly relevant in industrial and logistics contexts, where the continuous interaction between people, machines and physical environments requires solutions that minimize physical effort, reduce the risk of musculoskeletal injuries and improve operational performance (Salvendy, 2012). The principles of ergonomics, as described by the authors, such as Tosi (2020), thus contribute to a more sustainable working model, simultaneously promoting the well-being of operators and the overall efficiency of systems.

Physical ergonomics is the branch of ergonomics that studies the interaction between human beings and the physical factors of their working environment, such as posture, effort, repetition of movements, loads and the equipment used. In industrial and logistics contexts, this dimension becomes important due to the high physical demands associated with tasks such as lifting, manually transporting loads, restocking shelves and picking (Kadir et al., 2019).

According to McCauley-Bush (2011), physical ergonomics aims to reduce workers' exposure to biomechanical risks by improving the design of workstations and preventing musculoskeletal injuries. Bridger (2017) emphasises that excessive physical effort and incorrect postures are frequent causes of sick leave, especially in sectors where the work is manual and repetitive. Furthermore, Salvendy (2012) emphasises that the systematic application of ergonomic principles results not only in health benefits, but also in productivity gains, reduced errors and greater job satisfaction.

The ergonomic design of workstations must respect defined anthropometric limits, ensuring that tasks are carried out within the so-called comfortable reach zone, situated between approximately 90 and 120 cm from the ground, corresponding to the area between the operator's waist and shoulders (Scott, 2009). This configuration minimises biomechanical effort and muscle fatigue, reducing the risk of injuries associated with forced postures (Zink, 2009). According to McCauley-Bush (2011), ideal work surfaces should be adjusted to the height of the elbows, allowing the hands to act with precision and without excessive tension (Salvendy, 2012). In the case of repetitive tasks, it is recommended that objects be within a maximum radius of 50 cm in front of the body, avoiding flexion or torso twisting (Gášová et al., 2017).

The postures adopted during physical tasks have a direct impact on the biomechanical load applied to the body. Movements such as raising the arms above the shoulders, bending the trunk or twisting the neck deviate the body from its neutral position, increasing the risk of fatigue and musculoskeletal injuries (McCauley-Bush, 2011; Bridger, 2017). Repetition of these postures, even with moderate loads, particularly affects the lower back and upper limbs (Dul and Weerdmeester, 2008). The ISO 11228-1:2003 standard recommends that frequent tasks be performed with the spine in a neutral position and the arms close to the body, avoiding asymmetrical efforts. Sustained or inclined postures, such as squatting, require greater muscle activation and reduce efficiency, with negative impacts on operator comfort and performance ((Salvendy, 2012; International Organization for Standardization, 2003).

The aim of ergonomic risk assessment is to identify postures and working conditions that may pose a risk to the musculoskeletal health of operators. To this end, two widely used tools stand

out: RULA (Rapid Upper Limb Assessment) and REBA (Rapid Entire Body Assessment). RULA was developed by McAtamney and Corlett (1993) as a methodology for rapidly assessing the postures of the upper limbs, neck and trunk. Using a scoring grid based on direct observation of the task, the method provides a score between 1 and 7, indicating the degree of risk, where higher values suggest the urgent need for intervention. The REBA, proposed by Hignett and McAtamney (2000), focuses on the whole body and is particularly effective in assessing tasks involving the upper limbs, lower limbs, trunk and neck simultaneously. It classifies risk into five levels of action, allowing for a more comprehensive assessment of dynamic and complex postures, which are common in logistics and industrial contexts (McCauley-Bush, 2011). In addition, the NIOSH lifting equation makes it possible to quantify the risk associated with lifting tasks. Its result is based on the calculation of the Lifting Index (LI) (Equation 2.4) (Ansari and Sheikh, 2014).

$$LI = \frac{L}{RWL} \quad (2.4)$$

where:

- L is the actual weight of the load lifted (in kg),
- RWL is the recommended weight (*Recommended Weight Limit*), calculated by:

$$RWL = LC \times HM \times VM \times DM \times AM \times FM \times CM \quad (2.5)$$

The variables correspond to multiplication factors associated with the geometry and context of the survey:

- LC : base load,
- HM : horizontal distance,
- VM : vertical height,
- DM : vertical travel distance,
- AM : asymmetry angle,
- FM : survey frequency,
- CM : load grip quality (*coupling*).

A value of $LI > 1$ indicates that the task exceeds the recommended limits and requires ergonomic intervention (McCauley-Bush, 2011).

2.3 Automation in Inventory Management

The choice to address automation in inventory management arises from the concrete need to find effective solutions to the problem identified in this study: the manual and inefficient process of replenishing A-Frame dispenser channels. In this context, it is pertinent to explore the technologies that have contributed most to improving precision, reducing unproductive time and optimising logistics operations in environments with characteristics similar to the one analysed. Technologies such as RFID, warehouse management systems (WMS), IoT sensors and artificial intelligence were selected because they are among the most widely used and validated in practice in automation

processes applied to automated warehouses and pharmaceutical environments. Other less mature technologies or those with limited application were not analysed in depth, given their limited direct impact on the problem studied.

This section therefore aims to present an informed view of the role of automation in inventory management, not just as a market trend, but as a concrete response to the operational limitations observed in the A-Frame system under analysis.

Automation in inventory management has become a strategic concept in the modernization of supply chains, promoting operational efficiency, error reduction and real-time visibility of operations. Unlike conventional methods, these systems are capable of handling large volumes of data and transactions accurately, integrating technologies such as RFID, warehouse management systems (WMS), robotic picking, IoT sensors and artificial intelligence (Richards, 2017; III and Hackman, 2014). This advance is driven by the growing demand for reduced lead times, higher stock turnover and personalization of the customer experience.

In a broader context, these technologies are part of the Industry 4.0 revolution, where warehouses have been transformed into smart warehouses, highly connected digital structures in which sensors, actuators and analysis platforms ensure not only the control of inventory levels, but also their prediction and automatic replenishment (Elangovan, 2019). The introduction of systems such as A-frame dispensers, automated picking, and conveyor systems guided by computer intelligence has made it possible to achieve greater precision in operations, improve ergonomics for operators and reduce operating costs (Richards, 2017).

Furthermore, as Vaka (2024) points out, automation must be understood in an integrated way with distribution strategy and production planning, promoting a synchronized flow between stock levels, vehicle allocation and demand forecasting. Digitalization also makes it possible to implement approaches such as Vendor Managed Inventory (VMI) and continuous monitoring systems with RFID, which facilitate automatic replenishment based on real-time data.

However, despite the obvious benefits, implementing automated solutions requires a careful approach, adapted to the specific needs of each organization. As Madamidola et al. (2024) point out, the challenges of integrating inventory systems with other business processes still persist. Thus, automation is not just a competitive advantage, but an important requirement to ensure agility and sustainability in the logistics operations of the future.

2.3.1 A-Frame Dispensers

A-Frame dispensers are an advanced automation solution for the unit order picking process, especially effective in environments with a high volume of orders and small, high-turnover products. The name “A-Frame” derives from the physical layout of the equipment, whose structure is shaped like an “A”, Figure 2.2. Its physical structure is made up of vertical channels on each side, into which units of the same article (SKU) are placed. At the base of these channels there are ejectors which, by means of a signal from a control system, automatically release the product and its quantity directly onto a central conveyor which moves boxes or containers (Pazour and Meller, 2011).

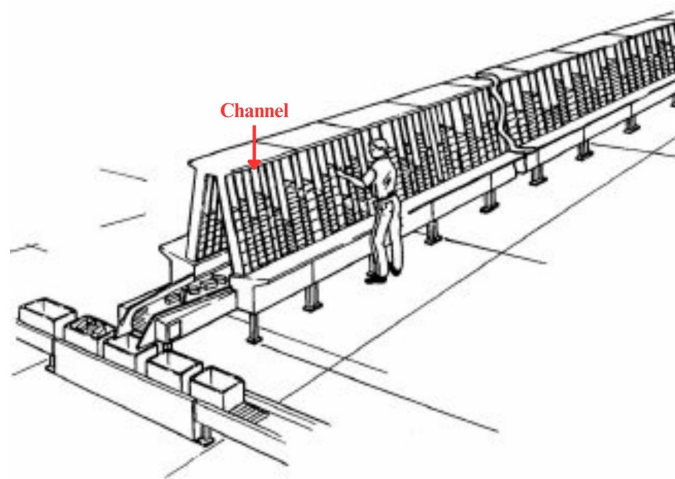


Figure 2.2: Depiction of an A-frame system (Pazour and Meller, 2011)

This type of system makes it possible to achieve high throughput rates with accuracy levels of over 99.9%, making it ideal for operations in industries such as pharmaceuticals, cosmetics, consumer packaged goods and e-commerce. According to Richards (2017), A-Frames are capable of processing up to 2,400 orders per hour, with very little or no human intervention in the picking process, which contributes significantly to reducing errors, increasing productivity and improving ergonomics in the warehouse.

Despite the high degree of automation in the picking process, the A-Frame channels are replenished manually by the operator. This manual replenishment is one of the system's main operational challenges, especially when there is a need to maintain a continuous picking flow. To mitigate this problem, several studies have explored order sequencing strategies that reduce the frequency of replenishment and minimize overloads on auxiliary operators (Boywitz et al., 2019). The success of the system thus depends not only on the automation of picking, but also on its integration with efficient and well-synchronized replenishment processes.

Sizing and organizing an A-Frame system requires a set of strategic decisions such as selecting the SKUs that will be assigned to the system, the number of channels allocated to each product and their location in the structure. According Meller and Pazour (2008), the choice of SKUs must take into account the volume of demand, the cost of replenishment, and the frequency of use, in order to optimize overall performance. In many cases, the installation of adjacent replenishment racks allows operators to replenish items without interrupting the operation of the system, improving operational efficiency.

It should also be noted that not all items are suitable for this type of system. Products with irregular shapes, excessive fragility or large dimensions are not compatible with the standardized structure of the channels. For these cases, alternatives such as zonal picking systems, collaborative robotics or manual picking should be applied (Boywitz et al., 2019). Even so, for items that meet the physical and logistical requirements of A-Frames, this technology represents an extremely effective and scalable solution.

In addition, the integration of A-Frames with warehouse management systems (WMS) is important because it ensures smooth operations and real-time visibility of stock levels. When properly configured, WMSs communicate directly with the dispenser system, program picking orders, monitor stock by channel and issue alerts for replenishment. Connectivity with technologies such as RFID or IoT sensors can also increase the degree of automation, aligning the system with the principles of smart warehouses and Industry 4.0 (Elangovan, 2019).

2.3.2 Stock Monitoring and Control Technologies

Modern inventory management requires ever greater visibility into the movement, location and status of products in real time. This need has driven the adoption of stock monitoring and control technologies, which not only enable continuous data collection, but also automate logistical decision-making. Systems such as the Warehouse Management System (WMS), RFID (Radio Frequency Identification), IoT (Internet of Things) and smart sensors represent fundamental principles for a more efficient, agile and resilient supply chain (Richards, 2017; Simchi-Levi et al., 2021b).

The WMS is an information system that manages, tracks and optimizes all material flows within the warehouse - from reception, storage and handling to picking, packing and shipping (III and Hackman, 2014). It can be integrated with automated systems such as A-Frame dispensers, automated guided vehicles (AGVs) and intelligent shelving, promoting continuous monitoring of inventory levels. Among automatic identification technologies, RFID stands out for eliminating the need for direct visual contact with products, unlike the traditional barcode. Composed of electronic tags and radio readers, RFID makes it possible to trace units in real time and with high precision, even in environments with a high density of items (Elangovan, 2019). (Myerson, 2015) adds that this technology is particularly useful in the pharmaceutical, food and fashion industries, where batch and expiry date control is critical.

The Internet of Things (IoT), on the other hand, elevates the concept of monitoring by allowing physical objects (such as shelves, boxes or even products) to be equipped with sensors capable of communicating data in real time. These sensors can capture variables such as location, temperature, humidity or weight, and transmit this information automatically to the central system (Elangovan, 2019; Simchi-Levi et al., 2021b). This continuous connectivity makes it possible to create intelligent logistics environments, where the system automatically detects deviations and triggers corrective measures without human intervention (Christopher, 2011).

Stock control technologies also contribute to better strategic decision-making, thanks to the ability to generate real-time data that feeds analytical systems. According to Simchi-Levi et al. (2021b), the use of interactive dashboards, performance metrics and predictive models based on machine learning makes it possible to anticipate shortages, identify consumption patterns and adjust replenishment policies dynamically. Despite the numerous advantages, implementing these technologies requires investment and careful integration with existing systems. Vaka (2024) stresses that effective automation depends not only on acquiring technology, but also on training teams, reviewing processes and clearly defining operational objectives.

2.4 Technologies for optimizing stock replenishment

The growing complexity of logistics operations and the need for fast and accurate replenishment in high-turnover environments have driven the development of advanced technologies for monitoring and managing stock. In this context, various solutions have emerged that aim to automate or support inventory replenishment, reducing manual effort, improving accuracy and increasing the overall efficiency of the system.

This section presents a study of three different approaches - automated vertical storage, artificial intelligence-based forecasting and visual monitoring with computer vision - which represent different paths to modernising stock replenishment processes.

2.4.1 Vertical Lift Modules in Automated Replenishment

Automatic vertical modules, classified as Vertical Lift Modules (VLM), are integrated storage systems that use height space to organise products in electronically controlled pull-out trays (Richards, 2017). These systems work with two storage columns between which moves a central lift that automatically removes and delivers the trays requested by the system (Frazelle, 2016) (Figure B.3 in Appendix B). The operation follows the goods-to-person principle, in which the material moves to the operator, significantly reducing the time spent physically traveling (Richards, 2017).

The structure of VLMs makes it possible to optimise the footprint and can reduce the storage footprint by up to 50% compared to conventional fixed shelving systems (Frazelle, 2016). This type of system is suitable for operations with a high turnover and diversity of items, allowing high storage density and easy access to inventory (Tompkins et al., 2010). The modular architecture of this equipment also facilitates the progressive expansion of storage capacity, adapting to the growth of the operation without significant structural reconfiguration (Richards, 2017).

In terms of performance, VLMs are capable of achieving pick rates of more than 90 lines per hour, with accuracy levels greater than 99%, representing a substantial gain over manual methods (Richards, 2017). Their integration with WMS allows for real-time updates, complete traceability, and automated control of inbound and outbound operations (Frazelle, 2016). Despite the benefits, this type of technology involves significant initial costs, as well as specific maintenance and layout adaptation requirements (Tompkins et al., 2010).

2.4.2 Computer Vision Systems for Inventory Monitoring

Computer vision is a technological tool that allows information to be extracted from images, and is particularly effective in industrial and logistical environments where repetitive visual tasks are to be automated (Davies, 2012). This system is based on the combination of optical sensors, digital cameras and image processing algorithms that identify and analyse visual patterns with high precision (Davies, 2012). In the context of stock monitoring, these technologies are used to visually detect the presence or absence of products on shelves or dispensers, replacing repetitive manual checking (Szeliski, 2022).

The process begins with image acquisition, where factors such as lighting, viewing angle and resolution are crucial to the system's reliability (Gonzalez and Woods, 2002). Next, segmentation and feature extraction algorithms make it possible to interpret the captured image and classify it according to defined criteria (Davies, 2012). These operations can be enhanced by artificial intelligence models trained on real images of the environment, which allows the system to be adapted to variations in product, packaging and layout (Szeliski, 2022).

According to Frazelle (2016), one of the main advantages of this approach lies in its non-intrusiveness, as it allows data to be collected without physical contact and with wide coverage. In addition, vision systems can be integrated with warehouse management platforms (WMS), enabling automatic inventory updates based on the visual interpretation of cyclically collected images (Richards, 2017). Tzampazaki et al. (2024) emphasises that these solutions are particularly useful in areas with high product turnover, where visual counting can replace or complement conventional replenishment systems.

2.4.3 Artificial Intelligence and Machine Learning

Machine learning is an area of data science that focuses on building mathematical models capable of learning from large amounts of data in order to make predictions or decisions (McMahon, 2023). The central idea is to provide an algorithm with a set of historical data, called a training set, so that it can identify recurring patterns in the available variables and use them as a basis for predicting future events or estimating results based on new observations (Vandeput, 2021). Unlike traditional statistical methods, which require the prior definition of a functional relationship between variables, machine learning models automatically adjust to the structure of the data, even when it is complex or non-linear (Goodfellow et al., 2016).

The learning process takes place iteratively. Initially, the algorithm generates predictions based on the input data. It then compares these predictions with known actual values, calculates the error made and adjusts its internal parameters to reduce this error. This cycle is repeated several times until the model achieves satisfactory performance, i.e. until it can predict with an acceptable level of error (Goodfellow et al., 2016; McMahon, 2023). After training, the model must be evaluated with data other than that used in training, known as the test set, in order to check its generalisation capacity and avoid the model merely memorising the original data, a phenomenon known as overfitting (Makridakis et al., 1983).

Machine learning algorithms for forecasting tasks can be grouped into three broad categories: regression-based models, models based on decision trees and neural models. Regression models seek to establish a functional relationship between explanatory variables and a dependent variable, and are useful when this relationship is relatively stable (Doan and Kalita, 2015). Tree-based models segment the data based on decision rules, making it possible to create predictions even in situations with multiple categorical or continuous variables (Shen and Cheng, 2022). Neural models, on the other hand, are inspired by the workings of the human brain and are capable of representing complex relationships between variables, especially when there are large volumes of data (Mishra and Gupta, 2017).

The choice of the most appropriate model depends on the type of data, the problem to be solved and the necessary balance between precision and interpretability (Vandeput, 2021). In all cases, it is essential to assess the model's performance based on error metrics such as MAE (Mean Absolute Error), RMSE (Root Mean Square Error) or MAPE (Mean Absolute Percentage Error) (Vandeput, 2021). These metrics provide a quantitative measure of the difference between the predicted value and the actual value, and are essential for comparing models and validating their effectiveness.

More recently, there has been a growing tendency to integrate predictive algorithms with prescriptive models, such as optimisation and decision automation systems. This integration allows a system not only to anticipate a future need, but also to propose or execute an action based on that prediction, contributing to more agile, adaptive and intelligent operations (Simchi-Levi et al., 2021a).

Chapter 3

Problem Statement

In order to understand the reasons behind the development of this project, it is necessary to contextualise MedLog's existing challenges, starting with a detailed description of its operational activity. Analysing the procedures currently adopted by the company makes it possible to identify the critical points of the process more precisely, as well as the opportunities for improvement, serving as a basis for defining strategies aimed at optimising them.

3.1 Operational Context and As-Is Analysis

MedLog is a pharmaceutical logistics company whose operations are divided into a set of stages that ensure the efficiency and organization of the company's activities. The following Figure 3.1 presents a diagram summarizing the five key stages of the operational flow: Reception, Storage, Picking, Expedition, and Distribution. Each of these stages plays a crucial role in optimizing logistics processes.

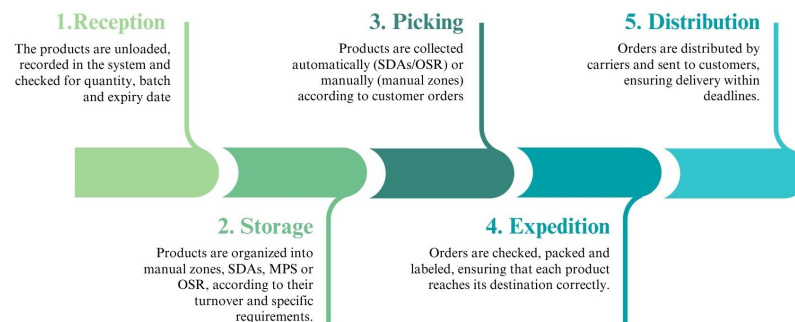


Figure 3.1: Storage Process Steps

The company's warehouse is organised into zones, each of which is designed to store products with similar characteristics. The operational areas include the Automatic Dispensing System (SDA or A-Frame), the Order Storage and Retrieval system (OSR), the manual zones (called M01, M02,

M03, M04, M05 and M06), the Manual Picking Station (MPS) and the Large Volume area (GV). The designation of each zone, as well as its numbering and type, can be found in Table 3.1.

Table 3.1: Station nomenclature

Station number	Designation	Description
001	M01	Manual Zone 01
002	M02	Manual Zone 02
003	M03	Manual Zone 03
004	M04	Manual Zone 04
005	M05	Manual Zone 05
015	EK and SK	Deviation station
016	M06	Manual Zone 06
062	SDA	A-Frame Dispenser 1
063	SDA2	A-Frame Dispenser 2
064	MPS	Manual Picking System
100	OSR	Order Storage and Retrieval
170	GV	Large volumes

The area known as SDA, or A-Frame, represents approximately 60 per cent of the warehouse's operational activity and is responsible for a fully automated picking process. The OSR, on the other hand, is an automatic order storage and retrieval system. In this area, the products are placed in specific trays and moved autonomously by the system, with all storage management being carried out automatically. However, the picking process is carried out manually, albeit in an optimised way, which justifies classifying the OSR as a semi-automatic picking zone.

The Manual Zone refers to picking carried out entirely manually, with products organised on static and dynamic shelves, without any support from automated systems. The MPS fits into this context, being made up of dynamic shelves similar to those in the A-Frame, but integrated into the OSR area. In this station, picking is carried out exclusively by the operator, as in the other manual areas.

The allocation of products to the A-Frame, OSR, and MPS zones is primarily based on turnover. Products with higher turnover are assigned to the A-Frame. Those with lower turnover, that is, with a daily average of fewer than five lines, are directed to the OSR or the MPS. In company terminology, a 'line' refers to a type of product included in an order, regardless of quantity, expiration date, or batch. In addition to turnover, other relevant factors are also considered, such as the type of packaging and the dimensions of the item.

Manual zones are particularly suitable for large products or for items which, although small, are more sensitive to automatic handling. This is the case, for example, with ointments, syrups or fragile packaging. The Large Volume area is designed for storing items of significant size, such as Canadians or large medical equipment.

Finally, the SK and EK stations act as diversion points for trays that have some kind of error. The main difference between the two is the origin of the trays: the SK station receives trays from the OSR, MPS and A-Frames, while the EK station handles trays from the corresponding manual zones.

The physical layout of these different zones and stations can be seen in Figure 3.2, which shows the general plan of the warehouse.

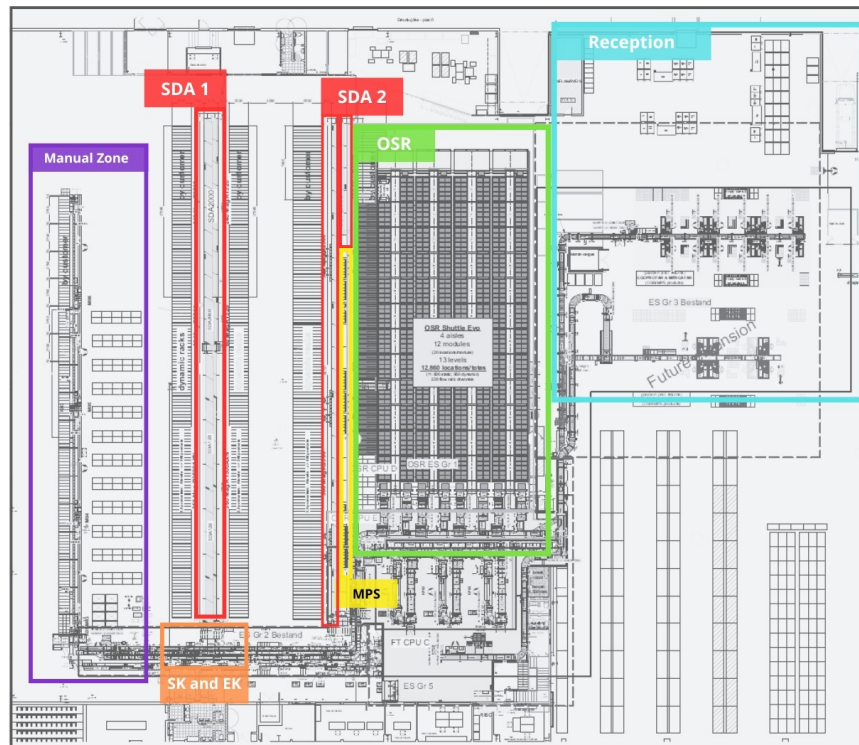


Figure 3.2: Layout of the Medlog Gondomar warehouse

3.1.1 Reception

Product reception is the initial phase of the logistics process, ensuring that items from suppliers are checked, recorded and correctly channelled.

The products are first unloaded at the reception dock. The responsible operators, located next to the unloading area, register the orders in the computer system and validate the conformity of the deliveries. During this operation, each order is associated with the appropriate storage area, taking into account the type of product.

The items are then transported into the warehouse and placed in the confirmation sections. At this stage, a detailed check is carried out to make sure that the products received actually correspond to those contained in the order. Information such as the batch number, expiry date and quantity received is recorded. If there are any discrepancies, the system automatically issues an error notification, blocking the storage of the product until the situation is clarified.

The total order entry remains pending until all the missing products have been located or justified, a situation that can occur, for example, when the same item is spread over several boxes with different batches. This procedure ensures that the data recorded accurately reflects the goods actually received, guaranteeing strict control of incoming stock. Although it involves manual steps, the validation system contributes significantly to reducing the likelihood of error.

Once verification is complete, the products are packed in boxes and placed on trolleys that are labelled according to the destination of each item. These destinations can include manual areas, urgent products or items allocated to the A-Frame. Each package is labelled with a yellow label containing the shelf code, the product name, the batch number and the destination zone. In certain cases, the label also includes information on the degree of urgency of the item. This organisation facilitates the subsequent work of the operators responsible for storage.

When the order is destined for the OSR or the MPS, the products are placed in appropriate grey trays and conveyed by conveyor belt to their destination. The detailed flow of this operation is shown in Figure C.1, in Appendix C.

3.1.2 Storage

The storage phase represents a fundamental stage in structured and efficient inventory management. The warehouse is divided into specific zones, organised according to well-defined operational criteria. Each shelf is assigned a unique location code, which makes it possible to precisely identify the positioning of products and ensure strict stock control. The allocation of items is determined on the basis of their category and particular storage requirements, ensuring not only the integrity of the products but also rational use of space. The distribution between automatic systems, such as the A-Frame, and manual storage areas is carried out strategically, with a view to maximising the overall efficiency of logistics operations.

The storage areas are methodically organised and numbered, and their function is delimited according to the nature of the products being stored. Zone M01 is for articles that require special storage conditions, including refrigerated goods, which are kept in temperature-controlled chambers, and substances subject to strict regulations, such as narcotics, psychotropic substances and high-value products. The latter are packed in their own vaults in order to guarantee high standards of security and legal compliance.

The other manual storage areas are organised based on their proximity to the order preparation zones, allowing operators to optimise travel times. The products with the highest turnover are located at station M02, while the items with the lowest shipping frequency are assigned to station M06. Each reference is associated with a localisation code, guaranteeing total traceability and facilitating the collection of items, which contributes to greater agility and operational efficiency.

During this phase, the storage and replenishment operators are responsible for transferring the products to their respective areas, ensuring that they are correctly placed in the designated locations. Whenever a shelf reaches its maximum capacity for a given product, the surplus is stored in an upper reserve area, duly signposted, making it available for immediate and efficient future replenishment. Figure 3.3 shows the respective positioning of the reserves.

As far as the OSR system is concerned, storage is fully automated and governed by specific stock management principles. Priority is given to the FEFO criterion, which determines the preferential dispatch of products with the closest expiry date. Whenever two or more items share the same expiry date, the FIFO method is applied, ensuring that they are dispatched in the chronological order in which they were received. In cases where, for operational reasons, it is not possible to apply these rules directly, the system adapts automatically, adjusting the movement of the trays based on shipping or replenishment needs, without compromising the organisation or efficiency of the warehouse. The detailed process of this phase is shown in Figure C.2, in Appendix C.

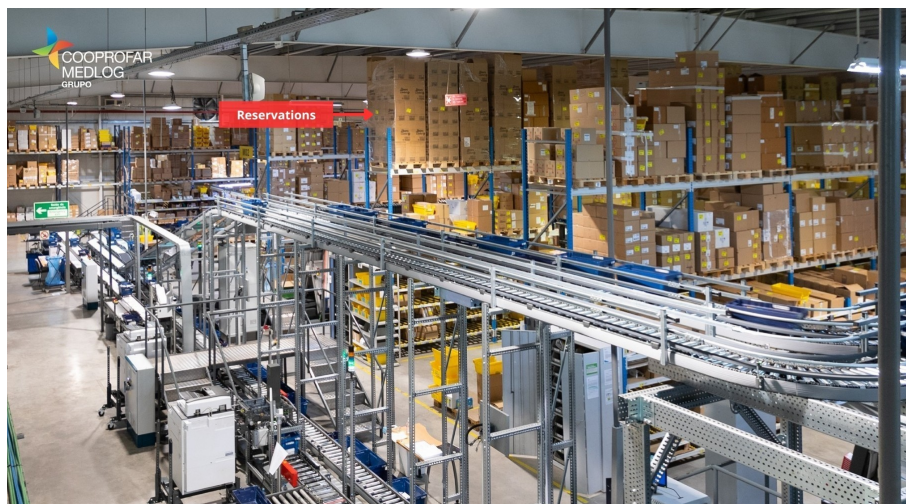


Figure 3.3: Image of the warehouse with reservations

A-Frames replenishment The A-Frames replenishment activity plays a central role in guaranteeing the continuity and efficiency of the automatic order preparation process. This operation is carried out after the initial reception and storage of the products, and is essential for keeping the channels supplied with adequate stock levels. Figure 3.4 shows a more detailed representation of the organisation of A-Frame systems. In front of the A-Frame are the dynamic shelves with the products intended to supply it, while at the rear of these shelves are the reserves, where surplus products that do not have space in the dynamic structures are stored.

The company has two A-Frame structures, called SDA1 and SDA2, each comprising several operational sections. Each shift, these sections are assigned to specific operators by the supervisor in charge. The job of these operators is to continuously monitor the channels, visually detecting which ones need replenishing, removing the products from the dynamic shelves and placing them in the appropriate channels. The replenishment process does not follow automatic criteria or stock management algorithms, it is carried out exclusively on the basis of the visual perception of the operator, who assesses the state of the channels and acts accordingly.

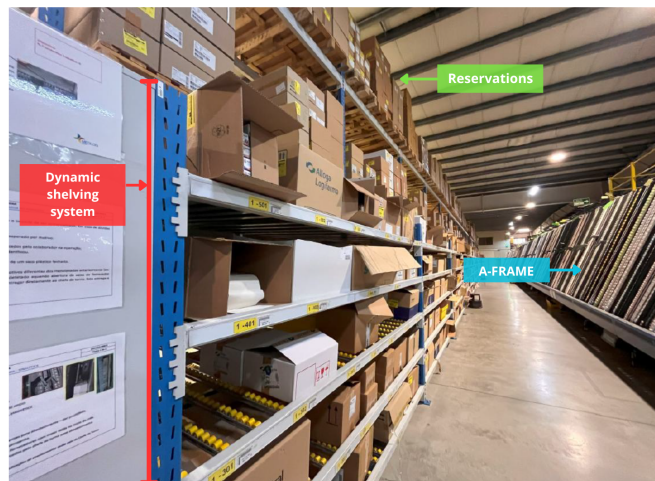


Figure 3.4: Organisation of A-Frame systems with dynamic front shelves and rear reserve area

Each channel is identified with a label containing relevant information, such as the product reference, batch number, booking location and, in some cases, restrictions associated with the weight of the package. To facilitate this identification, a system of colour-coded labels is used to help operators allocate products correctly, respecting the physical and structural limits of the channels.

During the replenishment process, situations may arise in which a particular item is of a different size to that expected, making it unsuitable for storage in the channel assigned to it. In these cases, the operator removes it and immediately informs the person responsible so that an assessment can be made and, if necessary, the specifications updated in the system. The flowchart representing this process can be found in Figure C.3, in Appendix C.

It is also important to note that orders containing more than thirty units of the same product are not processed automatically through A-Frame. In these situations, processing is transferred to a manual zone, in order to avoid immediately exhausting the channel and ensure the system's operational stability.

3.1.3 Picking

The picking phase varies according to the area of the warehouse and the type of product to be processed. All the orders for a given area originate from the same launch point, and the shift managers are responsible for accessing the current order book. Based on the proximity of the routes' departure times, they enter the orders into the system, starting the preparation process.

A-Frames In the A-Frame system, the picking process is fully automated, ensuring an efficient, precise and high-speed operation. Once the order has been entered into the system, the automatic dispensers receive the information corresponding to the products to be selected. The system triggers the injectors, which release the items from the storage channels onto the conveyor belts.

These dispensers are equipped with sensors that count and monitor the number of products released, ensuring that they are correctly directed along the conveyor belt. In the case of larger orders, the system carries out controlled vibration of the products in the trays, ensuring their correct arrangement and avoiding overlaps or counting errors.

After this stage, an identification label is applied to the tray, containing the order information and the corresponding route. Next, the invoice is placed inside the tray, the lid is put on and the security clips are applied, ensuring that the package remains sealed until it is delivered. Finally, the trays go to the dispatch area.

Manual Zones In manual zones, as the name suggests, the process is entirely manual. The operator consults the assigned order, collects the products from the indicated places and places them in the respective tray. For each item, he/she uses a barcode reader, which makes it necessary to read the product code and the tray, ensuring the traceability and accuracy of the process. Once collection is complete, the tray is placed on the conveyor belt and moved on to the next stages. In the GV area, the procedure is similar, except that the items are packed directly into boxes. Once they have been labeled for dispatch, they also go onto the conveyor belt.

MPS In the MPS system, the picking process is carried out manually, but with the support of a visual system that facilitates the operation. The operator moves to the dynamic shelving system where the products are stored and is guided by flashing lights (pick-to-light) that indicate the picking location and the destination dispenser. After removing the product from stock and placing it in the corresponding dispenser, the light switches to a steady state, confirming that the action has been successfully completed and that the product is ready to be included in the order. In this system, it is the operator who moves to the product.

OSR In the OSR system, the process is more automated. The trays in which the products are stored are automatically transported to the picking station according to a defined logic (such as FEFO or FIFO). When the tray reaches the preparation area, the operator is assisted by a pick-to-light system that indicates the quantity and the exact pick location. The operator removes the indicated products and places them on the despatch tray, which then goes to the conveyor line and enters the normal despatch flow. Unlike MPS, in OSR it is the product that goes to the operator, not the other way round.

Validation and Error Correction Before the shipping labels are applied, all orders go through a validation point. At this stage, non-conformities can be detected, such as missing products, empty channels or technical faults. When this happens, the trays are diverted to two error stations: Station SK, which receives trays with errors from the A-Frame and OSR systems, and Station EK, dedicated to manual zones.

In both cases, a deviation sheet is automatically generated, containing detailed information about the anomaly detected. The operator analyzes the occurrence and proceeds to resolve it.

If the fault is associated with a missing product, the operator goes to the corresponding shelf, collects the missing item, places it in the tray and reads the product and tray code again, validating the correction. The tray is then repositioned on the conveyor belt, resuming its journey through the shipping process.

The complete order picking and validation process, covering the different areas of the warehouse, is represented schematically in Figure C.4, included in Appendix C.

3.1.4 Expedition and Distribution

At this stage of the expedition, the trays reach the lower floor of the warehouse and are directed to one of two possible destination zones, being placed on the shelves according to their designated route. Additionally, in this phase of the storage flow, orders with errors follow a separate path.

Subsequently, the transport operators check whether any trays are missing. If they detect the absence of a tray, they conduct a verification in the error area. If the missing tray is found there, they report the issue so that the error can be properly analyzed.

Then the actual distribution process begins. The outbound logistics process is a crucial operation that involves loading the distribution vehicle with customer-bound orders while also handling the necessary transport documentation. This includes verifying and organizing all shipping and transport documents to ensure proper traceability of the goods. Additionally, the process encompasses checking customer information for each route, ensuring that every order reaches its designated destination efficiently and within the agreed time frame.

Furthermore, during this stage, empty trays are collected from pharmacies, health centers, and hospitals, following previous deliveries. Upon returning from their routes, drivers unload the empty trays, after which an operator reintegrates them into the new order flow, ensuring their reuse in the next distribution cycle.

3.2 Operational challenges and difficulties

In the course of analysing MedLog's logistics operations, operational constraints were identified that compromise the efficiency of the process. These challenges result from the high complexity of operations, decentralised inventory management and the physical limitations imposed by the working environment.

One of the difficulties encountered is the lack of standardised criteria for prioritising the replenishment of A-Frame system channels. The lack of clear guidelines leads to the situations when during the busiest periods, operators channel their efforts into replenishing less critical products, neglecting items whose absence compromises the system's overall performance. This problem is particularly aggravated in the case of less experienced operators, who face greater difficulties in identifying priority replenishment needs. The randomness observed in this process contributes to inefficient resource management and wasted operating time.

Another major problem is the time wasted at the SK station checking trays that have been diverted due to technical errors or missing units. Currently, this process requires manual intervention

on the part of the operators, which includes collecting the signalled tray, checking the quantities dispatched, comparing them with the quantities actually requested and then filling the tray after moving it to the respective storage area. As well as being time-consuming, this procedure proves to be inefficient, especially when the missing product is not available in the immediate stocks, forcing the operator to locate it manually and update the information in the system. This situation not only slows down the operational flow but also increases the likelihood of failures to meet dispatch deadlines.

The physical replenishment of A-Frame channels in itself presents a number of ergonomic and logistical challenges. Some of the products in reserve are stored in large boxes that are incompatible with the lower shelves. This limitation forces operators into demanding, sometimes repetitive and forced handling, which can cause physical fatigue and increase the risk of musculoskeletal injuries. What's more, for operators of shorter stature, access to the upper areas of the shelves is more difficult, jeopardising the fluidity of operations and compromising comfort and efficiency.

The combination of these factors shows that there are structural weaknesses in the stock replenishment and control process, which make it difficult for the automated system to function efficiently. The absence of a prioritisation logic, combined with ergonomic limitations and excessive dependence on manual tasks, highlights the need to reformulate current procedures.

Chapter 4

Data Analysis

This chapter presents the analysis that formed the basis of the diagnosis of the A-Frame system, corresponding to the first two phases of the methodological work defined at the start of the project. The first part focused on direct observation of the physical organisation of the channels, the way the products are distributed and the procedures associated with their replenishment. This analysis made it possible to identify certain patterns in the arrangement of items and to hypothesise the origin of the deviations found.

In the second part, operational data extracted from the company's internal system was collected and processed. This data provided a clearer perspective on the frequency and impact of the deviations detected, allowing a more objective assessment of the scale of the problem. The aim was to cross-reference the information gathered in the field with the indicators obtained, in order to better understand the limitations of the current system and its effects on logistics performance.

The work carried out at this stage served as the basis for the proposals presented in the following chapters and played a fundamental role in defining intervention priorities.

4.1 Diagnosis of A-Frame organization

As part of the methodology adopted, a detailed diagnosis of the operation of the A-Frame system was carried out in order to assess the adequacy of product allocation in relation to actual operational requirements. This automatic distribution system is a central element in the order preparation process, so its efficient use, adjusted to demand and compatible with the physical limitations of the channels, is an important requirement for guaranteeing high levels of productivity and quality of service.

Constitution of A-Frames The A-Frame, located on the Gondomar logistics platform, is made up of two separate units, called SDA1 and SDA2. Together, these units comprise a total of 2070 channels, of which 2066 are operational, with four channels currently inactive.

Each unit has a structural configuration consisting of wider and lower channels, referred to as large channels, and narrower and taller ones, known as small channels, arranged on opposite

sides. In total, the system comprises 1288 large canals and 778 small canals. SDA1 has 634 large channels and 628 small channels, while SDA2 has 654 large channels and only 150 small channels. The two A-Frame units are installed side by side, occupying a total length of approximately 60 meters. This differentiated configuration gives each unit specific operational characteristics, which will be understood through the physical layout shown in Figure 4.1.

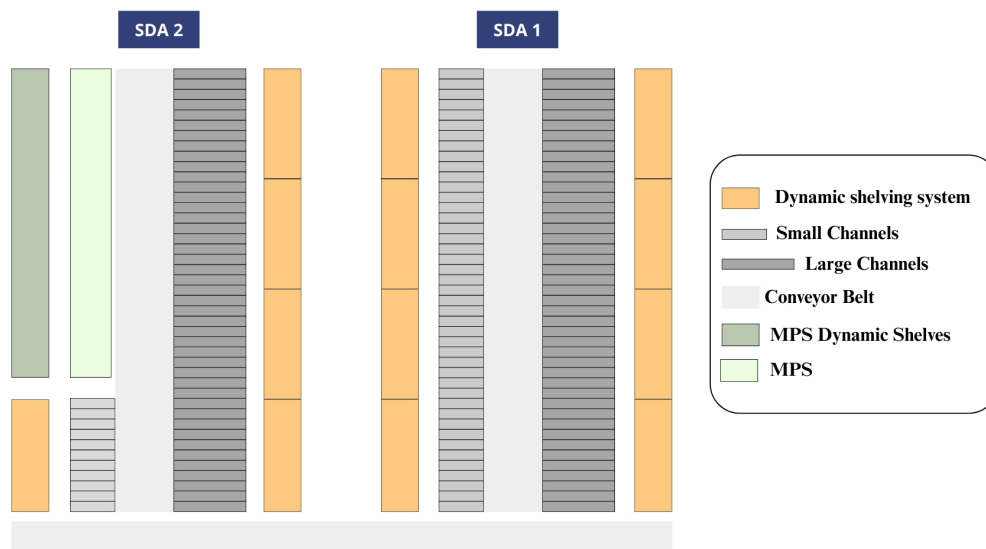


Figure 4.1: Representation of A-Frames

Although both units serve the same operational purpose, their construction differs in a way that affects the allocation of products. SDA2 is more recent and technically more advanced than SDA1. Certain products, due to their packaging characteristics (such as fragility or height), can only be stored in SDA2. If placed in SDA1, these items could suffer damage during dispensing, as the injectors in this older unit are metallic rather than plastic. This limitation requires special care when deciding which products are suitable for each unit.

Organisation of SKUs in the A-Frame The products stored in the A-Frame can be associated with one or more channels, depending on their operational needs. The number of channels per product is controlled sporadically and adjusted based on consumption and capacity criteria. The analysis carried out showed that a product can occupy between 1 and 12 channels of different types. As illustrated in the graph in Figure 4.2, the majority of products are associated with just one channel, followed by cases with two channels. The remaining higher values refer to a small number of products, which mostly correspond to items that are sold more frequently and in greater quantities

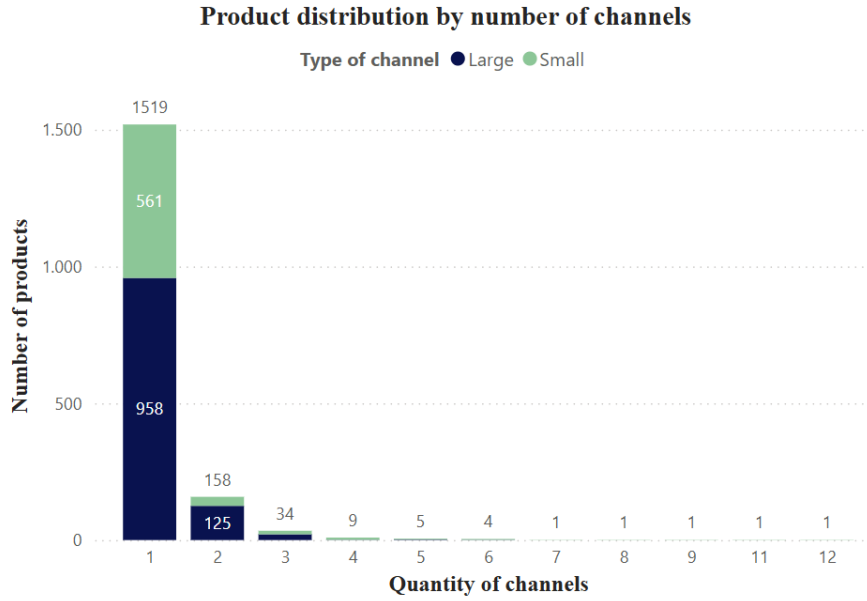


Figure 4.2: Distribution of products by number of channels assigned

The autonomy of the channels assigned to each product was analysed, based on the ratio between the average quantity shipped per day and the maximum capacity available for that product in the A-Frame. Total capacity is obtained by multiplying the number of channels allocated, N_{channels} , by the maximum quantity that each channel can store for the respective product, Q_{channel} :

$$\text{Total Capacity} = N_{\text{channels}} \times Q_{\text{channel}} \quad (4.1)$$

From this value, it was possible to calculate the autonomy of the products, expressed in number of days, using the following formula:

$$\text{Autonomy (days)} = \frac{\text{Total Capacity}}{\text{Average quantity dispatched per day}} \quad (4.2)$$

This calculation made it possible to estimate the number of channels needed to guarantee at least one day of autonomy without the need for refuelling. The results presented in Table 4.1 show that 162 products did not have enough capacity to cover a full day's operation, which highlights situations of undersizing. On the other hand, products were identified whose autonomy exceeds three days, occupying channels that could be reallocated to items with higher rotation and which currently require replenishment more than once a day.

This analysis reinforces the idea that a careful reorganisation of the allocation of channels in the A-Frame could bring significant gains in terms of logistical efficiency. Allocating channels according to the consumption behaviour of each product would make it possible to reduce shortages, optimise available resources and minimise the effort associated with replenishment. However, the allocation strategy cannot be limited to the channels themselves. It is also necessary to consider the availability of space in the dynamic shelving system behind the A-Frame (see Figure 4.1). This

Table 4.1: Distribution of products by number of days of autonomy without replenishment

Autonomy (days)	Number of Products
< 1 day	162
= 1 day	337
= 2 days	319
≥ 3 days	916

is the location from which operators manually pick the products used to replenish the channels. A product with high rotation that lack sufficient reserve space may create operational blockages, even if it is well positioned in the dispensing system.

Therefore, good A-Frame management involves not only choosing the most suitable channel for each item, but also ensuring the upstream conditions for replenishment are in place, balancing automation efficiency with the physical constraints of the storage layout.

Supplying the channels In addition to quantitatively analysing the allocation of products, an assessment was also made of the practical operation of the system, with a particular focus on the channel replenishment procedures. The estimated average time to replenish a channel is 2 minutes and 44 seconds, a figure that can vary depending on various operational factors, such as the size of the channel, the specific storage capacity of the product (associated with its volume) and the experience of the operator responsible for the task.

This average time, multiplied by the number of daily refuellings, represents a significant operational burden. The team assigned to this operation varies throughout the day and is adapted according to the workload planned for each time slot. Table 4.2 shows the distribution of the number of operators responsible for refuelling the channels, by time slot.

Table 4.2: Number of operators allocated to A-Frame replenishment by time period

Time Period	Number of Operators
09:00 – 11:00	6 to 8
11:00 – 15:00	2 to 3
15:00 – 18:00	3
18:00 – 03:00	1

Based on this average time of 2 minutes and 44 seconds per channel, and taking into account the number of operators present on each shift, it was possible to estimate the system's daily refuelling capacity. The results indicate that the total number of channels replenished per day varies between 736 and 899, depending on the actual availability of operators in each period. This variability is directly related to human resource management and daily fluctuations in demand, and is adjusted according to operational needs at any given time.

Ergonomics and working conditions As mentioned above, during the functional analysis of the logistics process it was identified that the task of replenishing the A-Frame system is not limited to placing product in the automatic channels, but also involves manually collecting units from the dynamic shelving system. This task, which is repetitive in nature, exposes operators to significant physical risks that justify the application of ergonomic assessment tools.

The boxes handled vary in weight from 1.5kg to 18kg. They are cardboard packages without ergonomic handles and range in size from 150 × 150 × 100mm to 500 × 400 × 300mm. Operators carry out this task several times a day, often continuously. The units can be removed from shelves with heights of more than 1.80 metres, which requires lifting the load with raised arms and keeping the load away from the axis of the body.

In order to quantify the ergonomic risk of this operation, the Lifting Index equation (NIOSH) was applied, which estimates the effort according to seven critical factors (Ansari and Sheikh, 2014). Based on direct observation and characterisation of the workstation, the following parameters were estimated in Table 4.3.

Table 4.3: Parameters, descriptions and multipliers used in the Lifting Index calculation

Parameter	Description	Value	Multiplier
<i>L</i>	Actual weight of the lifted load	18 kg	–
<i>LC</i>	Reference load constant	23 kg ^a	–
<i>HM</i>	Horizontal distance from hands to midpoint between ankles during lift	35 cm	0.78
<i>VM</i>	Vertical height of hands at start of lift	180 cm	0.83
<i>DM</i>	Total vertical travel distance of the lift	70 cm	0.93
<i>AM</i>	Angle of torso rotation during lifting	30–45°	0.81
<i>FM</i>	Lifting frequency (number of lifts per minute over 2 hours)	1 lift/min	0.85
<i>CM</i>	Coupling quality (grip type based on box design)	Cardboard box without handles	0.90

^aThe value of 23 kg corresponds to the Reference Load Constant defined by NIOSH. It is a standard value used as the baseline in the RWL calculation, assuming ideal lifting conditions such as waist-level height, load close to the body, good grip, low frequency, and no trunk rotation.

With these values, the maximum recommended weight (RWL) obtained was approximately 8.58kg, resulting in a Lifting Index of 2.10. This value is significantly above the safety limit (LI > 1), indicating that the task exceeds the effort considered acceptable and is associated with a high physical risk.

In addition to the physical load calculated, the posture adopted by the operators during the task was also assessed. The application of the RULA methodology revealed that the effort falls mainly on the upper limbs, since the arms are often raised above shoulder level, with trunk flexion and extension movements (McAtamney and Corlett, 1993). Although the exact score was not formally

assigned, it was noted that the postures correspond to an action level of 3 or higher, which indicates the need for changes to the task.

In addition, the REBA tool was used to assess whole-body exposure (Hignett and McAtamney, 2000). During the collection of boxes, the operator often adopts inclined postures with half bent knees and twisting of the trunk, while making significant physical effort. This combination of factors indicates a medium to high risk situation, justifying short-term corrective measures. This ergonomic analysis corroborated the complaints voiced by the operators themselves during on-site contacts, validating the perception of physical discomfort associated with this task.

The analysis carried out on the A-Frame system identified a series of structural and operational limitations that jeopardise the efficiency of the logistics process and the well-being of the teams involved. The technical differences between the two units (SDA1 and SDA2), associated with the physical characteristics of the products and the distribution of the channels, impose restrictions that must be taken into account in the day-to-day management of the system. It was found that the autonomy of many items is insufficient to cover a complete operating cycle, requiring frequent replenishments and penalising productivity.

At the same time, the physical constraints of the dynamic shelving systems and the effort required of operators when manually replenishing channels exacerbate the impact of these limitations. The ergonomic assessment confirmed the existence of high physical risks, justifying the implementation of corrective measures in the short term. This analysis is therefore an important basis for identifying operational deviations and defining the proposals for improvement presented in the following chapters.

4.2 Data Collection and Analysis

The analysis carried out at this stage was based on operational data for the year 2024, taken directly from the company's ERP system. Although the information covered all relevant activity, the data was scattered across multiple non-integrated tables, with no explicit relational structure and, in many cases, only available indirectly. Identifying the necessary elements required defining specific criteria, applying conditional filters and creating relationships between tables based on common but often denormalised or inconsistent fields.

This process involved intensive data modelling work using Power BI, in which logical links were established between the various data sets. The relational structure obtained is represented in Figure D.1, included in Appendix D. The analysis was complemented with the use of Microsoft Excel, applied for specific validations, additional calculations and checking the consistency of the consolidated data.

In addition, an interactive dashboard was developed using Power BI to analyse deviations over the course of the year. This dashboard included indicators on the distribution of deviations by station, time interval, type of error and article, allowing for the consolidation of previously dispersed data without structured or historical treatment. The information represented on the dashboard came from operational records that had not previously been systematically analysed.

The combination of the data processed and the tools used made it possible to build a set of operational indicators that underpin the analysis described in the following sections. The detailed description of the developed dashboards is presented in Appendix D.1.

Description of the 2024 analysis In 2024, 11,789,263 lines were processed on the Gondomar platform. Each line corresponds to a type of product included in an order, regardless of the quantity requested, the batch, the expiry date or the respective price. This volume represents a monthly average of 982,439 lines, reflecting the high operational pace of the logistics unit. The monthly distribution of this indicator is shown on the Appendix D dashboard, in Figure D.2, allowing a more detailed analysis of the evolution over the year, including metrics such as monthly growth and standard deviation.

In the same period, 102,052 deviations were recorded at stations SK (station 015) and EK (station 017), which corresponds to 0.87 per cent of the total number of lines processed. These deviations were the result of various causes, including: lack of product in the A-Frame channels, counting errors by operators in manually dispatched orders and technical faults associated with the operation of the equipment, such as incorrect sensor readings.

Analysing the monthly variation in the number of lines processed and the deviations recorded shows fluctuations associated with seasonal factors, employee holiday periods and stock shortages on the part of suppliers, as illustrated in Figure 4.3. The Figure D.3, in Appendix D, shows these discrepancies in more detail, revealing that there is no constant proportional relationship between the volume of lines processed and the number of deviations. The proportion of deviations varies significantly from month to month, with no uniform pattern.

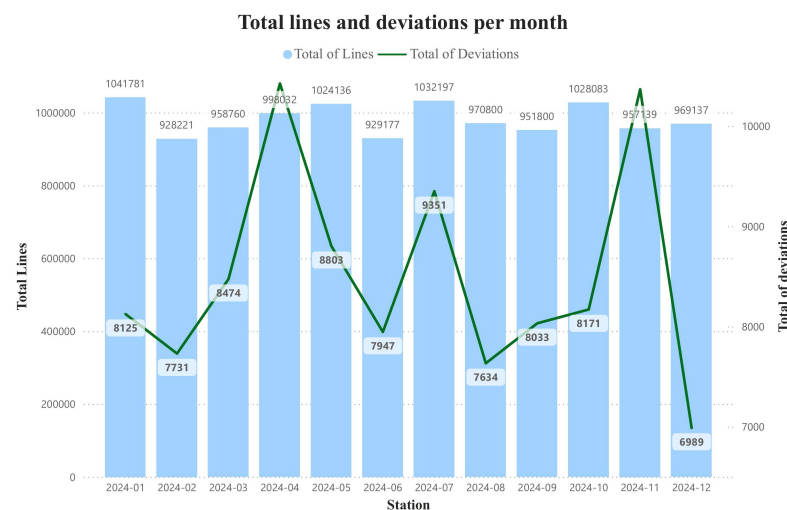


Figure 4.3: Number of lines and deviations per month

Deviations at SK station Analysing the distribution of deviations by station (identified and described in Table D.1 of Appendix D) revealed a greater concentration in stations 062 and 063, corresponding to the A-Frames, which recorded the highest number of occurrences throughout the

year, accounting for 98.72% of all deviations, as illustrated in the graph in Figure 4.4. In total, these two stations processed 6,554,040 lines, of which 100,754 had deviations, corresponding to an incidence rate of 1.28%.

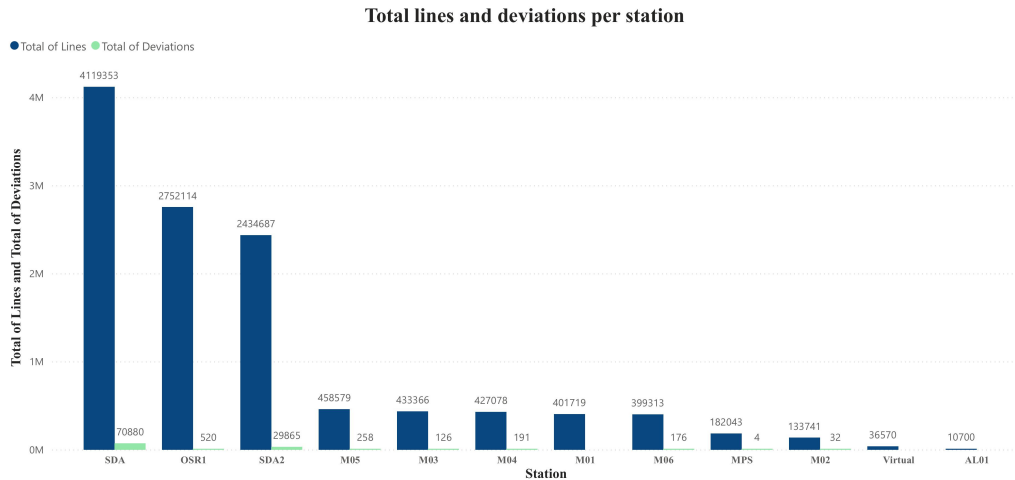


Figure 4.4: Number of lines and deviations per station

In order to analyse this further, the most recurrent type of deviation was identified, classified into two categories: deviations due to lack of product and deviations due to technical failure. As shown in the dashboard of the Appendix D, in Figure D.3, it was found that 94.7% of deviations were caused by a lack of product in the channels, while only 5.3% resulted from technical anomalies associated with the operation of the equipment.

In addition, operational behaviour was analysed throughout the day, based on the average number of deviations recorded during the year. As illustrated in Figure 4.5, there is a significant increase in the number of deviations in the intervals between 9am and 11am, and between 11pm and 1am.

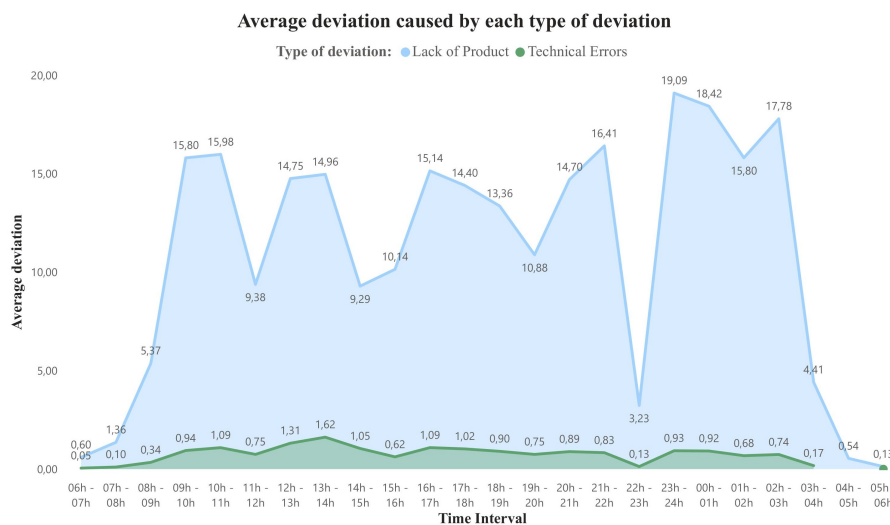


Figure 4.5: Average deviation caused by each type of deviation

These intervals coincide with the periods immediately after the main peaks in logistics activity, during which the number of lines processed increases significantly. The average number of lines processed per hourly interval is shown in Figure 4.6.

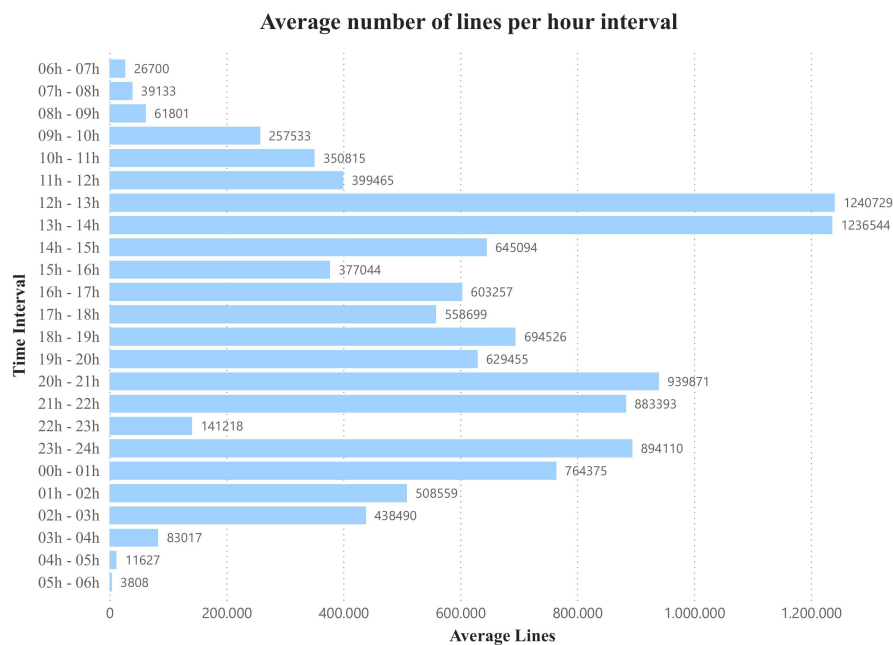


Figure 4.6: Average number of lines per interval

Most of the company's logistics operations are concentrated between 11am and 2pm and between 8pm and 11pm. During these periods, A-Frame's channels are subject to intensive consumption, which leads to their partial or total emptying. In the following intervals, there is often a lack of immediate supply, especially at night, as the system is not replenished at the same rate as the products are dispatched. This dynamic results in a higher incidence of deviations due to lack of product in the moments after peak operations. Thus, there is a direct relationship between the volume of lines processed, the emptying of the channels and the increase in the rate of deviations in subsequent periods.

Deviations in A-Frames In the context of A-Frames, the two types of deviations described above were again considered. Deviations due to lack of product refer to situations in which the channel is empty or in which, although there are units of the article in the warehouse (namely in the reception area), they are not available on the A-Frame's dynamic shelves for immediate replenishment.

The analysis made it possible to conclude that only 4.07% of the deviations recorded at these stations correspond to technical faults, while the remaining 95.93% are the result of product unavailability in the channels. This result highlights the need to strengthen the supply and stock

monitoring processes in these units. The dashboard shown in Figure D.5 of Appendix D represents the monthly distribution of the types of deviation, as well as their daily incidence throughout the year, using a heat map.

The time during which trays remain diverted was also analysed, i.e. the interval between the moment when the diversion occurs at the SK station and the moment when the tray is reintegrated into the circuit after its correction. This metric makes it possible to quantify the accumulated delay in the normal dispatch flow. It was found that average diversion times vary significantly throughout the year and are influenced by the type of error. Technical faults are generally easier to identify and correct, while deviations due to product shortages require more complex intervention, as they involve the operator travelling to the reserve area, locating the missing item and checking its availability, which considerably lengthens the resolution time.

Figure 4.7 shows the hourly distribution of the average deviation time, showing a significant increase in the early hours of the morning and late evening. These peaks coincide with periods when the availability of operators at the SK station is low, making it difficult to check and correct deviations in good time. On the other hand, during periods of greater operational intensity, resolution times tend to decrease as more human resources are allocated to these tasks.

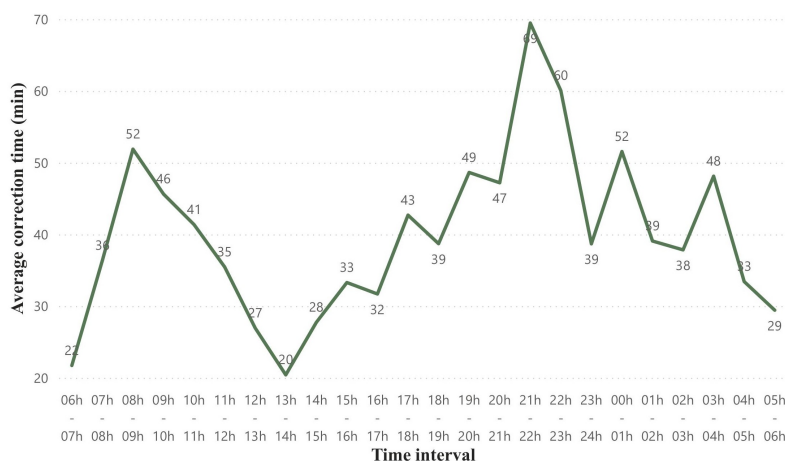


Figure 4.7: Average deviation time per hour

In this context, the average diversion time is not a sufficiently representative metric, as it depends heavily on the presence of operators at the time of the event. Figure D.7, shown in the respective dashboard, allows us to visualise this variation in greater detail. As an indication, the data analysed shows that the average time needed to correct a deviation, from its identification to the tray's return to the circuit, is 2 minutes and 36 seconds, although this figure may vary depending on the location of the product and the availability of resources at the time of the event.

The boxplot diagram shown in Figure 4.8 illustrates the distribution of diversion times by station, showing the presence of a significant number of outliers, particularly at stations associated with A-Frames. These outliers confirm that the average time is substantially influenced by periods when there are no operators available to resolve the deviations. The average times were 41.52 minutes for A-Frame 1 and 40.12 minutes for A-Frame 2, respectively.

This analysis shows that the lack of a systematised criterion and automated system for monitoring stock levels in the channels contributes not only to the high frequency of deviations recorded, but also to the length of the respective resolution process. During critical periods of the operation, this limitation is particularly important and can lead to significant delays in the overall dispatch process.

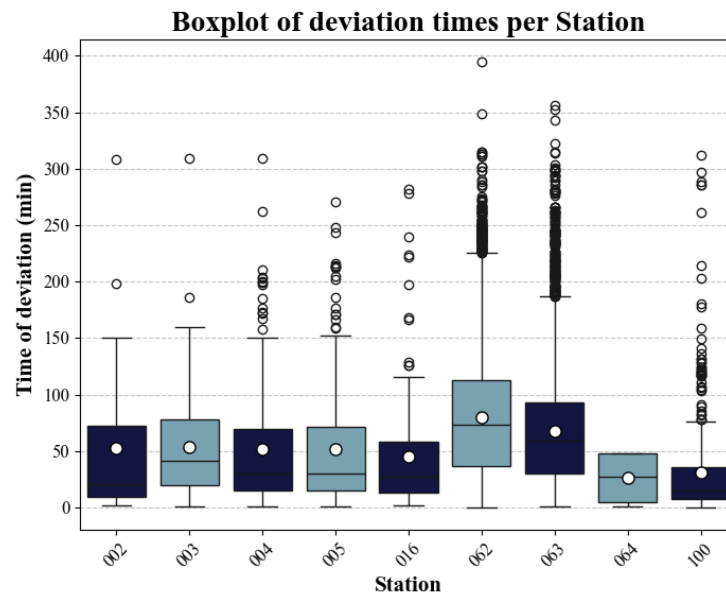


Figure 4.8: Boxplot of deviation times per Station

4.3 Practical Implementation of ABC/XYZ Analysis

In order to segment the products based on their relative importance, an ABC analysis was carried out, supported by a multi-criteria approach combining data normalisation, the TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution) and Linear Programming. This methodology made it possible to classify the products in the A-Frames in a balanced way and according to the Pareto principle, according to which approximately 20% of the items represent approximately 80% of the total value handled Kheybari et al. (2019).

Normalisation of variables The variables used to apply this analysis were extracted from the original inventory file provided by the company and were selected on the basis of their logistical relevance. The four quantitative variables chosen were as follows:

- The *Qty / day (outbound)*, which represents the average daily quantity sold of each product - a direct indicator of demand;
- The *Stock available*, which represents the current level of inventory;
- The *Days in stock*, which estimates the time until stockout based on average demand;
- The *Lines / day (outbound)*, which indicate how often the product is moved.

These variables are on heterogeneous scales (days, units, frequencies, etc.), so they had to be normalised beforehand. The *min-max* normalisation method was used, which transforms the values into the $[0, 1]$ interval, according to the expression in Equation 4.3.

$$x_{ij}^{\text{norm}} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (4.3)$$

where x_{ij} is the original value of the variable j for the item (in our case product) i , and x_{ij}^{norm} is the corresponding normalised value.

Calculation of weights with Shannon entropy With the data normalised, the Shannon entropy of each criterion was calculated in order to assign objective weights to the variables according to their discriminatory capacity. This method assumes that criteria with greater diversity (i.e. lower entropy) provide more information and should therefore be given greater weight in the analysis.

For each variable j , the probability distribution of its normalised values was calculated by:

$$P_{ij} = \frac{x_{ij}^{\text{norm}}}{\sum_{i=1}^m x_{ij}^{\text{norm}}} \quad (4.4)$$

with m representing the total number of products. The entropy values were then obtained from Equation 4.5.

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m P_{ij} \cdot \ln(P_{ij}) \quad (4.5)$$

Next we calculated the degree of diversity $d_j = 1 - e_j$ and the final weight of the criterion j , w_j , by normalisation:

$$w_j = \frac{d_j}{\sum_{j=1}^n d_j} \quad (4.6)$$

The weights w_j obtained were then used to weight the criteria in the TOPSIS method.

Calculating the performance index with TOPSIS With the weights defined, the TOPSIS method was applied, which makes it possible to classify alternatives based on their relative distance from a positive ideal solution (best possible case) and a negative ideal solution (worst possible case). For each product i , the weighted distances to the ideal solutions were calculated using Equations 4.7 and 4.8.

$$D_i^+ = \sqrt{\sum_{j=1}^n w_j \cdot (x_{ij}^{\text{norm}} - x_j^+)^2} \quad (4.7)$$

$$D_i^- = \sqrt{\sum_{j=1}^n w_j \cdot (x_{ij}^{\text{norm}} - x_j^-)^2} \quad (4.8)$$

where $x_j^+ = \max_i x_{ij}^{\text{norm}}$ and $x_j^- = \min_i x_{ij}^{\text{norm}}$. The final TOPSIS score was calculated as follows:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (4.9)$$

The closer C_i is to 1, the more desirable the overall performance of the product. The products were then ordered by C_i in descending order.

ABC Segmentation by Objective Linear Programming Once the products had been sorted on the basis of TOPSIS scores, they were segmented into A, B and C classes. The aim of this segmentation was not only to respect the hierarchy defined by the performance scores, but also to ensure compliance with the Pareto rule - according to which approximately 20% of the products concentrate 70 to 80% of the value moved.

To this end, an Objective Linear Programming model was developed, inspired by the formulation presented by Kheybari et al. (2019). The model considered three binary indicators for each product i as decision variables: A_i , B_i and C_i , corresponding respectively to their allocation to classes A, B or C. By definition, each product could only belong to one of the classes, i.e. the sum $A_i + B_i + C_i$ would necessarily be equal to 1.

The model formulation included simultaneous targets for two dimensions: (1) the number of items per class and (2) the accumulated value of each class, this value being measured on the basis of the average daily volume handled. Target percentages were set for both dimensions: 20% of items and 70% of value for class A; 30% of items and 20% of value for class B; and 50% of items and 10% of value for class C.

The objective function was designed to minimise the total difference, in absolute value, between the targets set and the results achieved in each class. The notation d_k^- and d_k^+ was used to represent, respectively, the negative and positive deviations relative to each of the targets. Thus, the model's objective function was defined by:

$$\begin{aligned} \min \big(& d_{A,\text{val}}^- + d_{A,\text{val}}^+ \\ & + d_{B,\text{val}}^- + d_{B,\text{val}}^+ \\ & + d_{C,\text{val}}^- + d_{C,\text{val}}^+ \\ & + d_{A,\text{num}}^- + d_{A,\text{num}}^+ \\ & + d_{B,\text{num}}^- + d_{B,\text{num}}^+ \\ & + d_{C,\text{num}}^- + d_{C,\text{num}}^+ \big) \end{aligned} \quad (4.10)$$

Each pair of deviations is associated with one of the model's six goals: - cumulative value of class A, B and C; - number of items in A, B and C.

The constraint equations were formulated to ensure that the deviations absorbed the difference between the actual value and the desired target. For example, in the case of class A, the target in terms of value moved was expressed as:

$$\sum_{i=1}^N v_i \cdot A_i + d_{A,\text{val}}^- - d_{A,\text{val}}^+ = TPA \cdot \sum_{i=1}^N v_i \quad (4.11)$$

where v_i represents the daily movement value of the product i , and TPA the target percentage, i.e. 70% for class A. The same logic was applied to classes B and C, and to product totals by class, using the variable N for the total number of products and the coefficients TNA, TNB, TNC for the targets in terms of quantity (e.g. 20%, 30%, 50%).

The inclusion of deviation variables allowed the model to find a feasible solution even when the objectives conflicted with each other, while minimising the accumulated deviations. This type of modelling is especially useful in real-life contexts where it is rarely possible to meet all the goals simultaneously with precision.

Given that the original model presented by Kheybari et al. (2019) is highly complex and requires specialised solvers, this implementation adopted a simplified heuristic version, coded in *Python*, using the `PuLP` library. The code is shown in Appendix E.

This classification model was key to ensuring that the final segmentation not only reflected inventory management priorities, but also respected a theoretically justified and operationally viable distribution.

XYZ classification based on demand variability In addition to the ABC analysis, the XYZ classification was implemented in order to assess the predictability of demand for each product. The coefficient of variation (CV) was used, which relates the standard deviation of demand to the average, calculated according to Equation 4.12.

$$CV_i = \frac{\sigma_i}{\mu_i} \quad (4.12)$$

with μ_i the average and σ_i the standard deviation of the variable `Qtd / day (output)`. The thresholds defined for segmentation were:

- Class X: products with $CV < 0,5$ - stable demand;
- Class Y: $0,5 \leq CV \leq 1$ - moderate demand;
- Class Z: $CV > 1$ - irregular and unpredictable demand.

The application of this analysis enabled the classification of the various A-Frame products according to the ABC/XYZ methodology. The corresponding classification, along with the demand curve used for the XYZ segmentation, is presented in the dashboard shown in Figure D.8 of Appendix D.

Following the classification of products based on their turnover and demand level, a comparative analysis was carried out between turnover rate and the deviations recorded due to stock shortages in the A-Frame channels. This analysis is presented in the dashboard in Figure D.8 of Appendix D, where each product's classification and the distribution of deviations throughout the analysis period can be viewed using a heat map representation.

Subsequently, the Pareto rule was applied (as shown in the dashboard in Figure D.9 of Appendix D) to identify the items responsible for 80% of the total deviations. The results revealed 431 products which, over the year under analysis, accounted for a total of 77,902 deviations attributed to stock shortages in the automated system.

Based on this cross checking of data, it was concluded that 41.76% of the products belong to class A, 37.36% to class B and 20.88% to class C. These figures suggest that high and medium rotation products are the main culprits in the occurrence of deviations, contrary to the common perception that this phenomenon is more associated with low rotation items.

In addition, a relationship was established between the classification of products and the number of channels assigned to each one in the A-Frame. In keeping with the logic of Pareto analysis, it was found that of the total of 2,069 existing channels, 577, corresponding to 27.9% , concentrated 80% of the deviations observed. As can be seen in Figure 4.9, the majority of deviations are associated with products that only have one channel, totalling 338 articles. Among the products with two channels, 67 were identified, while only one product with a high record of deviations is spread across 11 channels, which is an exception.

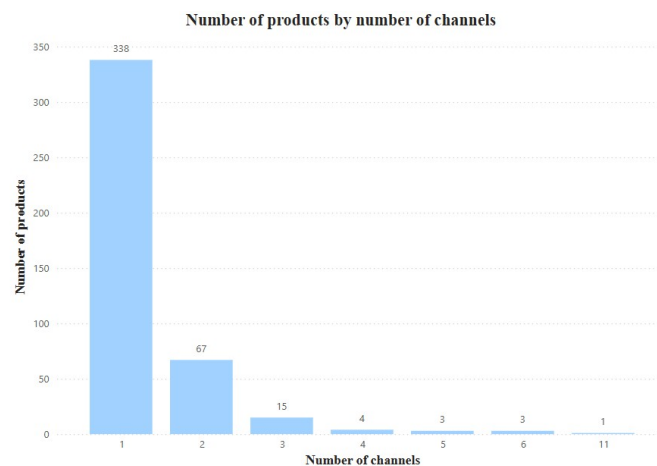


Figure 4.9: Number of products by number of channels

The collection, modelling and analysis of operational data for 2024 enabled the consolidation of a robust informational basis on the deviations recorded at the logistics unit. The development of an interactive Power BI dashboard, complemented by statistical evaluations and ABC/XYZ classification, revealed previously unmonitored behavioural patterns, facilitating the identification of the main causes of deviations and their temporal and structural distribution. These findings serve as the foundation for the operational improvement proposals presented in the following sections.

Chapter 5

Proposed Solutions and their Evaluation

This chapter presents three different technological solutions designed to improve the performance of the replenishment process: a solution based on an automated vertical storage system (Kardex), a decision support tool based on artificial intelligence algorithms (Wiimer) and a continuous visual monitoring system using computer vision cameras (Inovesense). Each proposal is described in detail, taking into account its technical and operational assumptions and its applicability in the context of the company.

The second section of the chapter is dedicated to operational analysis and simulation of the impact of the solutions presented. To this end, a discrete event simulation model was developed that reproduces the system's behaviour in different scenarios based on real data. This approach makes it possible to quantify the effect of each solution on the main logistics performance indicators in an objective and comparable way.

This is followed by a financial analysis in which the initial investments, operating costs and expected return of each alternative are estimated. Finally, the Balanced Scorecard is used as a decision support tool, integrating the different assessment dimensions to identify the solution best suited to the organisation's needs and capabilities.

This chapter therefore brings together the proposals for improvement developed in the project and assesses their potential to make the replacement process more efficient, reliable and sustainable.

5.1 Proposed Solutions

Following the diagnostic analysis, a survey of available technological solutions on the market was conducted, with the aim of identifying viable proposals to improve the channel refilling process of A-Frame systems. The main purpose of this stage was on exploring alternatives that could reduce manual effort, minimise errors associated with the current procedure, and enhance the overall efficiency of the operation.

To this end, an exploratory approach was adopted, which included analysing the state of the art in logistics automation systems, direct contact with suppliers specialising in automated warehouse equipment and consultation with other companies in the pharmaceutical sector with similar logistics operations. Through this triangulation of sources, it was possible to obtain a comprehensive perspective on current practices and the most innovative solutions applied in other contexts.

It was noted, however, that the market still has significant limitations when it comes to automating the control of stock levels in individual A-Frame channels. One of the cases analysed was the solution currently available in the company, associated with the A-Frame system supplied by KNAPP, which uses RFID technology. This system is based on the manual parameterisation of each channel and the active intervention of the operator whenever a supply takes place. According to the procedure in place, the operator identifies the channel using the handheld terminal, counts the number of units inserted and records this quantity after reading the product code. Although it works as a control mechanism, this process has proved to be time-consuming, susceptible to counting errors and represents a significant burden for operators, especially in channels that require handling large volumes of product.

In an attempt to identify more automated alternatives, it turned out that some of the most advanced A-Frame systems integrate infrared sensors directly into each channel. These sensors enable automatic level detection based on the reading of an optical beam, signalling when the channel is below a certain threshold. However, this technology involves a high installation cost, frequent maintenance and requires the system to be dimensioned for warehouses with high stock autonomy, in which the channels hold enough volume for several days of operation, which does not correspond to the operational reality observed in this project.

Given the lack of standardised solutions that met the specific needs of the company under analysis, alternative proposals were investigated and adjusted, taking into account technical limitations, operational requirements and the degree of practical feasibility. The options presented seek to strike a balance between automating the monitoring of stock levels, improving the quality of information to support decisions and keeping investment within the strategic limits defined by the organisation.

5.1.1 Kardex: Using a Vertical Carousel Module

The solution presented by Kardex, a global intralogistics company specialising in automated solutions for warehouses and materials handling systems, consists of installing an automated storage system of the Vertical Carousel Module (VCM) type (Figure 5.1), with the aim of serving as an intermediate storage area between stock and A-Frame systems. This system is intended to replace the current dynamic shelving infrastructure used for storing and feeding products into the A-Frame.



Figure 5.1: Vertical Carousel Modules | Kardex Megamat 180 / 350 / 650

The equipment operates on the basis of a vertical carousel system made up of rotating shelves, where cardboard boxes containing products of different sizes, as well as specific plastic boxes, are stored in a compact and accessible way. Interaction with the system is via a tactile console located on the front of the equipment, allowing the operator to insert or remove products in a practical way. Navigation is assisted by light signalling and confirmation buttons, providing simple, safe and intuitive use. The Figure F.1 in Appendix F shows a visual representation of the proposed system.

This proposed solution transforms the replenishment workflow by introducing an intermediate, automated storage layer between central stock and the A-Frame. Rather than replenishing directly from the main warehouse, operators interact with the Kardex unit, which acts as a managed buffer zone. This design facilitates better organisation, streamlines operator movement, and enables systematic inventory control.

5.1.2 Wiimer: Application of Artificial Intelligence Algorithms

Wiimer, a Portuguese company specialized in data analytics and intelligent process optimization, proposes a solution to improve the efficiency of A-Frame channel replenishment through the development of an analytical tool that supports restocking decisions. This tool is based on the creation of a product replenishment index, calculated using a Machine Learning (ML) model trained on historical data from the company's ERP system. By analyzing trends and forecasting consumption, the system can anticipate replenishment needs in advance.

The approach introduces a predictive and data-driven logic into the replenishment workflow. Instead of relying on the empirical judgment of operators, the tool identifies products at greater risk of stockouts and automatically prioritizes them. This enables more informed, timely actions and reduces the number of incomplete orders caused by replenishment failures.

The proposed model is integrated with the company's internal database via Power BI's Direct-Query functionality, ensuring real-time access to relevant data. The system operates based on up

to ten attributes, previously validated and mapped by the technical team. The replenishment index itself follows a simple scale (e.g., 0 to 100), designed to trigger visual alerts through a dashboard interface.

Once the algorithm has been designed and validated, a Power BI dashboard is developed to present the most urgent restocking needs in a clear and intuitive format. The dashboard includes filters by A-Frame (SDA1 or SDA2), by product, and by criticality level, and is accessible to internal users, prioritizing simplicity and readability.

The implementation of the project follows an agile methodology over a total duration of nine weeks, as shown in Figure F.2 in Appendix F. The work plan is structured into the following phases:

- Mapping and technical feasibility of data
- Algorithm design and testing
- Validation with real data
- Construction of the final dashboard
- Delivery of the complete solution

5.1.3 Inovesense: Monitoring with Computer Vision Cameras

The third solution outlined to improve the A-Frame refuelling process is the implementation of an automated visual monitoring system based on computer vision technology. This approach replaces the current empirical method used by operators to check channel levels and enables real-time detection of product quantities in each A-Frame channel.

Inovesense, a company specialized in industrial artificial vision and intelligent automation, is the implementation partner responsible for this proposal. To carry out the solution, the use of industrial cameras from the Cognex brand is suggested, a manufacturer widely recognized for its reliability and robustness in industrial settings. These devices are equipped with high-resolution sensors and advanced image processing capabilities, allowing them to accurately identify visual patterns, contours, and fill levels within the A-Frame channels. This ensures continuous and precise stock level control.

The operation of the system is illustrated in Figure 5.2, showing how the cameras integrate with the A-Frame structure. Each camera is positioned to visually monitor up to fifteen channels simultaneously. The system continuously captures images and processes them using computer vision software. These images are then compared to pre-defined thresholds. When a channel's level drops below the minimum acceptable value, a replenishment request is automatically triggered and transmitted to operators through portable data terminals (PDTs).

To ensure consistent and reliable detection, the cameras must be strategically installed to guarantee full visibility over the monitored channels. In addition, the system requires a complementary lighting setup to provide optimal visual conditions for accurate image capture and processing.

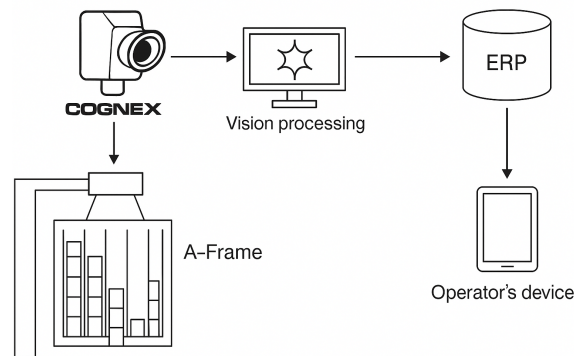


Figure 5.2: Integration of the computer vision system with the A-Frame replenishment process

This solution introduces a real-time, sensorless detection layer to the replenishment process. By continuously monitoring product visibility, it reduces the dependence on manual verification and increases responsiveness to stock shortages. The cameras and software are seamlessly integrated with the ERP system, ensuring that the existing operational workflow remains intact while enhancing its automation capabilities.

5.2 Operational Analysis and Simulations

To support a consistent and objective evaluation of the proposed solutions for improving the A-Frame replenishment process, a simulation model was developed to replicate the operational behaviour of the current system and test the expected impact of each alternative. Simulation was chosen as a methodological tool due to its capacity to reproduce complex logistical dynamics without disrupting real-world operations, enabling controlled experimentation under identical conditions.

The model is based on a discrete-event simulation approach and reflects key processes such as order generation, stock consumption, channel replenishment, operator activity and system deviations. It integrates detailed logic for each of the three solutions under consideration, Kardex vertical storage modules, Wiimer's predictive algorithm and Inovesense's computer vision system, allowing for quantitative comparison grounded in actual operating data.

By simulating a complete year of operation, the model generates performance indicators that help assess the effectiveness of each solution in improving system availability, reducing replenishment delays and minimising stockouts.

5.2.1 Modeling and Simulation of the A-Frame System

In order to characterise and evaluate the current performance of the A-Frame system in a logistically automated operations environment, a simulation model based on discrete events was developed. This modelling approach enables the accurate representation of real operational behaviour, incorporating both deterministic constraints (such as tray capacity and replenishment rules) and stochastic phenomena (such as order generation, technical deviations, and variable operator availability).

The simulation spans a time horizon of 365 consecutive days, with a resolution of 10 minutes per simulation step, totalling over 52,000 discrete time steps per product throughout the year. At each time step, the system checks whether a product order is generated, processes the request, and evaluates whether any channel requires replenishment. This step-based structure simulates the dynamic flow of operations in real time, while ensuring that all decisions and consequences (such as stock depletion or operator delays) are recorded and updated.

Each order line corresponds to a request for a specific product and is placed on a tray, the physical unit that moves through the A-Frame. Trays can carry up to 30 units of products originating from the A-Frame. In accordance with actual operational rules, orders containing more than 30 units of a single product are excluded from the automated system and fulfilled manually. This rule is implemented as a filtering condition in the simulation's order generation logic.

Although trays in real operation may contain products sourced from other warehouse zones (e.g., OSR, MPS, manual areas), the simulation model focuses exclusively on the A-Frame. This means that only the portion of the order assigned to the A-Frame (up to 30 units per tray) is simulated. This abstraction allows for a clearer understanding of the performance of the A-Frame system without confounding variables from other warehouse areas.

The model is parameterised using five data files provided by the company, as shown in Table G.1 in Appendix G. These datasets include product characteristics, historical order data, technical deviation statistics, and replenishment configurations. At each time step, a probability function determines whether an order is generated, based on the historical number of lines per day and weighted by time-of-day activity patterns. Periods of higher activity, such as between 11:30am and 2:30pm or 8:00pm and 12:00am, are more likely to generate orders, while periods like 3:00am to 7:00am are associated with lower probabilities.

When an order is generated, a quantity between 1 and 30 units is requested. If sufficient stock exists in the product's associated channels, units are withdrawn evenly from the available channels. If stock is insufficient to fulfil the order, a deviation is recorded and the tray is redirected to the error correction station (station SK).

Even when stock is available, a technical deviation may occur with a historical probability of 4%, simulating machine-related issues such as misreads or alignment faults. These deviations are not corrected immediately and contribute to system inefficiency.

The replenishment process in the simulation mirrors the behaviour of operators as observed in real operations. Each operator can handle one replenishment task at a time, and replenishment times follow a uniform random distribution between 120 and 300 seconds. The number of available operators varies by hour based on shift data, with more resources allocated during peak times and fewer during night shifts and breaks.

Importantly, there is no prioritisation logic guiding replenishment: operators choose channels at their discretion, which can result in critical channels being left empty while others are restocked. This reflects the current behaviour in the warehouse and is a key factor contributing to inefficiencies.

The simulation tracks a wide set of variables for each product, as summarised in Table G.2 in Appendix G, including total requests, simulated deviations, number of empty channel events, number of replenishments, and total waiting time for replenishment.

The core efficiency metric used is the deviation rate, calculated as:

$$\text{Deviations\%} = \frac{\text{Simulated Deviations}}{\text{Total Requests}} \times 100\% \quad (5.1)$$

At the end of each simulated day, the simulation exports operational KPIs, such as number of orders, deviations (technical and stock-related), replenishments made, total replenishment waiting time, and average operator availability. These indicators are exported to Excel for graphical analysis and comparative assessment.

Given the modular nature of the simulation model developed, it was possible to implement different operational scenarios through controlled changes in the code. These scenarios represent plausible technological or strategic interventions aimed at improving the replenishment process of the A-Frame.

The Python simulation code implementing the base model logic, including data ingestion, replenishment rules, and KPI tracking, is fully documented and provided in Appendix G.

Scenario 1: Kardex VCM Solution The first scenario corresponds to the implementation of a vertical automated storage system, such as Kardex, for products with high turnover. In the simulation, this technological improvement was represented by reducing the stochastic interval of replenishment times from 120 to 300 seconds to 60 to 150 seconds, reflecting the increased efficiency of such systems. Additionally, although no priority logic was introduced, faster replenishment implicitly improves the service level for critical products.

Scenario 2: Solution of a Wiimer ML Algorithm The second scenario introduces an intelligent prioritisation logic into the replenishment process, based on product turnover. In this context, it is assumed that the products with the highest daily turnover should be replenished more quickly in order to guarantee their continuous availability. This prioritisation was integrated into the model by dynamically adjusting the replenishment time: products classified as having high turnover were associated with a stochastic time of between 100 and 200 seconds, while the rest remained within the original range of 200 to 300 seconds.

Scenario 3: Solution using Inovasense VC Cameras The last scenario involves adopting a camera system capable of automatically detecting when a channel reaches empty status. To represent this new behaviour in the model, the probability of refilling whenever a break occurs has been increased, setting it at 90%, in contrast to the conditioned randomness existing in the base scenario.

The scenarios were built with the same input parameters and intentionally maintained the same order structure and hourly distribution of operators. The only changes were to the behaviour associated with the replenishment logic. This approach ensures direct comparability between the

results obtained in each scenario. The performance indicators corresponding to each simulation are exported in independent files, allowing detailed comparative analysis from both an operational and economic point of view.

5.2.2 Operational Analysis

The operational analysis of the proposed solutions aims to provide a structured and comparative understanding of their impact on the replenishment process within the A-Frame system. This analysis includes both simulation-derived results and a qualitative assessment of the solutions' effects in terms of reliability, flexibility, and impact on warehouse staff. The goal is to offer a comprehensive and evidence-based perspective on the strengths and limitations of each solution, supporting an informed strategic decision.

Impact on Logistics KPIs

The impact of the proposed solutions on operational performance was assessed on the basis of a set of key indicators defined according to the main challenges identified in the A-Frame system replacement process. The KPIs considered were: the average number of deviations per day, the percentage reduction in deviations compared to the baseline, the reduction in average waiting time for replenishment, the improvement in service level, and the percentage of avoided stock-outs. These KPIs directly reflect the weaknesses identified in the diagnosis, namely instability in replenishment, lack of prioritisation of critical products and the high manual burden associated with checking stock. Moreover, they represent the most relevant criteria for the company's decision-making.

Table 5.1 shows the results obtained in each simulated scenario. The data summarises the relative performance of the Kardex, Wiimer and Inovesense solutions compared to the current situation (Base).

Table 5.1: Estimated impact on key operational KPIs

Indicator	Base	Kardex	Wiimer	Inovesense
Average deviations per day	287	190	173	162
Reduction in deviations (%)	–	82.00%	47.20%	68.92%
Reduction in average waiting time (%)	–	44.10%	28.00%	37.50%
Service level improvement (%)	–	+20%	+10%	+15%
Avoided stockout rate (%)	–	75%	50%	60%

The results show that all the technological solutions tested contributed to a significant improvement in the indicators assessed, albeit with different levels of impact. Kardex achieved the best overall performance, particularly in reducing deviations and replenishment times, which reflects its highly automated nature and integration with the ERP system. The Inovesense solution

showed significant gains, notable for its real-time detection capacity, with a direct impact on reducing faults and breakages. Finally, Wiimer's proposal, demonstrated more moderate improvements compared to the other two approaches.

Replenishment Efficiency and Reliability in Detecting Needs

The three solutions analysed propose different approaches to identifying the need for replenishment in A-Frame channels. Kardex uses automatic control of stock levels, based on predefined minimums integrated into the ERP. These parameters are defined using classic inventory management models, namely the EOQ, safety stock and replenishment point, as illustrated in the Table in Figure H.1 of Appendix H. Wiimer uses predictive logic, calculating a replenishment rate based on consumption history. Inovesense, on the other hand, uses a real-time visual detection system using industrial cameras.

Despite the differences, all these approaches make it possible to replace manual control with systematic and automatic mechanisms, increasing the consistency of the process and reducing dependence on the operator's judgement. We can see that all the solutions has a direct impact on improving operational performance. Kardex stands out for its complete automation of the process and two-way communication with the ERP, supported by well-defined replenishment parameters. Inovesense demonstrates a high level of responsiveness thanks to its immediate and continuous detection of needs. In turn, Wiimer shows that significant gains can be achieved simply by improving decision-making and planning, without the need for physical changes to the process.

Flexibility, Scalability and Spatial Impact

Kardex Kardex offers a modular solution that can be implemented in phases. A selective approach focusing on A-turnover products, responsible for around 80% of daily order lines, can be adopted initially. In terms of spatial efficiency, Kardex enables a significant reduction in warehouse footprint. While a traditional dynamic aisle occupies approximately 150 m², the equivalent capacity using Kardex modules would require only 46.45 m², representing a 69% reduction in floor area. Each module occupies 5.8 m² and provides a useful volume of 37.22 m³, compared to 315 m³ for a full dynamic shelf. This gain enhances the flexibility of warehouse layout and leaves room for future expansion. The technical specifications of the equipment are detailed in Appendix H.

Wiimer Wiimer is highly flexible and scalable, as it does not require physical infrastructure. Its algorithm can be adjusted to any number of channels and products, and its dashboard allows filtering by A-Frame, product or urgency level. Implementation can be gradual and easily adapted to operational priorities.

Inovesense Inovesense offers scalability in terms of camera-based coverage, but requires physical installation, cabling and calibration. Each camera can monitor about 15 channels, allowing

incremental expansion. However, the expansion effort is more complex than with Wiimer and more infrastructure-dependent than Kardex.

Impact on Operators

Kardex The implementation of the Kardex solution in the A-Frame replenishment process results in a substantial improvement in the ergonomic conditions of operators, mitigating the physical risks associated with restocking tasks. Unlike the current situation, where operators perform repetitive lifting motions from high shelves—requiring overhead arm movements and significant torso flexion the Kardex system allows all operations to be performed at waist level, eliminating awkward postures and excessive effort.

From a biomechanical perspective, the Lifting Index (LI) was recalculated using the NIOSH methodology, applying the same parameters as before but adjusting the key factors to reflect the new working configuration. The vertical height of the lift (VM) decreased from 180 cm to approximately 100 cm (average working height with Kardex), and the horizontal distance (HM) was reduced from 35 cm to around 20 cm, as the operator no longer needs to extend their arms to reach the load. The coupling quality remained the same, since cardboard boxes without ergonomic handles are still used.

With these new values, the Recommended Weight Limit (RWL) increased significantly to 15.75 kg, reducing the Lifting Index from 2.10 to approximately 1.14. This improvement brings the task closer to the safety threshold, reclassifying it from high to moderate risk. Table H.1 in Appendix H presents a summary comparison of the most relevant NIOSH parameters before and after the implementation of the Kardex solution.

Additionally, a qualitative posture assessment using the RULA and REBA methodologies confirmed a significant reduction in upper limb and spinal strain. With the Kardex system, movements are performed within the comfortable reach zone, and operators handle products close to the body, maintaining a neutral posture. This change lowers the risk level according to ergonomic assessment tools, promoting a safer work environment, with reduced injury potential and improved operational efficiency. The new process proposed using the Kardex is represented schematically in Figure H.4 of Appendix H.

Wiimer Wiimer changes the way operators plan their activities, not how they physically perform them. The system generates prioritised restocking suggestions, reducing reliance on experience or informal judgement. Operators still execute tasks manually, but with improved clarity and fewer errors. Some basic training is needed to interpret dashboard outputs.

Inovesense Inovesense streamlines operator intervention by sending alerts only when replenishment is strictly necessary. This reduces the frequency of unnecessary verification rounds and improves efficiency. However, the physical effort remains unchanged. Training is simple and involves understanding how to read system alerts and respond promptly.

5.3 Financial Analysis

The purpose of this financial analysis is to gauge the economic impact of implementing each of the proposed solutions for improving the supply process of the A-Frame system. To this end, not only the initial investment costs are taken into account, but also the expected operating costs and the estimated return associated with each alternative.

This approach allows for a rigorous and objective comparison of the financial effort required by each solution, in conjunction with the anticipated operational benefits, thus supporting a well-supported decision-making process in line with the organisation's reality.

Initial Investment The initial investment includes all the direct costs associated with acquiring, installing and implementing the solutions. The following elements were considered for each proposal:

- Main equipment (hardware or software development);
- Installation and integration costs;
- Licensing (where applicable);
- Initial user training;
- Accessories required for operation (such as lighting or portable devices).

The estimated initial investment values for each solution are shown in Table H.2 in Appendix H

In the case of Kardex, the proposed investment involves the acquisition of nine Megamat 350 modules, each with an estimated unit cost of €67,000, as indicated in Table H.3 of Appendix H. The total base investment amounts to €603,000, covering the installation of modules across the three operational sides of the A-Frame. In addition to the base cost, two optional enhancements are proposed: a parcel grouping table with six illuminated displays (€4,900), and modular boxes and dividers for better shelf organization, the cost of which varies with quantity.

Wiimer's investment totals €24,500 plus VAT, billed in two phases of 50% each. This covers the delivery of a predictive algorithm, a Power BI dashboard, and technical documentation. Post-implementation maintenance services are not included in the base price but are offered optionally at an annual cost of €3,000 to €5,000. Wiimer's solution also assumes the company will provide visualisation devices for operator access. As shown in Table 5.2, this includes either fixed industrial screens or industrial tablets. These devices are not part of Wiimer's proposal but are essential for complete system use.

Table 5.2: Estimated cost of visualization devices (company responsibility)

Device Type	Unit Price (€)	Total Estimated Cost (16 units)
Fixed industrial screens	€400	€6,400
Industrial tablets	€600–800	€9,600 – €12,800

The Inovesense solution includes the deployment of 138 Cognex industrial cameras (covering 15 channels each), with unit costs ranging between €2,500 and €4,000, totalling between

€345,000 and €552,000. Complementary equipment includes a lighting system, installation and ERP integration, and 5–8 handheld devices, totalling €4,800–8,000. The estimated total investment is between €429,800 and €660,000, as detailed in Table 5.3. This system ensures full visual coverage of the A-Frame channel structure without disrupting current logistics flows.

Table 5.3: Estimated investment for the computer vision camera solution

Item	Estimated cost (€)
Cognex cameras (138 units)	345,000 – 552,000
Lighting system	30,000
Installation, assembly, and ERP integration	50,000 – 70,000
Handheld devices (5 to 8 units)	4,800 – 8,000
Total estimated	429,800 – 660,000

Operational and Maintenance Costs Beyond the initial investment, it is important to consider the operational and maintenance costs associated with the use of each solution over time. These costs directly impact the operational budget and must be analyzed for a realistic estimate of each alternative's total cost of ownership.

The following factors were considered:

- Technical maintenance (preventive and corrective);
- Energy consumption;
- Software licensing and updates;
- Initial and continuous operator training;
- External technical support (helpdesk).

Table H.4 in Appendix H gives an annual estimate of the main operating costs associated with each solution. The figures indicated for Wiimer include information provided directly by the partner, namely the annual maintenance cost. For the Kardex and Inovesense solutions, and for the other elements not specified in the proposals, estimates based on market values and solutions with similar characteristics were considered. These figures serve as a comparative reference and may vary depending on the utilisation regime and service contracts defined by the company.

In conclusion, it can be seen that the Kardex solution has moderate operating costs, Wiimer stands out as the most economical option in terms of running costs, while the Inovesense proposal involves significantly higher operating costs, resulting from the system's technical complexity and ongoing maintenance requirements.

Implementation Time The time needed to implement each solution is an important factor in the decision-making process, as it directly influences the start of operational gains and the planning of the transition from the current system. The implementation duration includes the preparation, installation, testing and commissioning phases. Thus, Kardex's implementation time was set at 12 to 18 weeks, Wimmer's at 9 weeks and Inovesense's at 10 to 12 weeks.

Kardex has the longest implementation time due to the production of the modules, international shipping, physical installation and integration with the Power Pick software. The preparation of the warehouse space and testing also contribute to this extended timescale. Wiimer's proposal offers the shortest implementation time because it follows an agile approach and is exclusively software-based. Finally, Inovesense has an intermediate timeframe of between 10 and 12 weeks. This period includes installation of the Cognex cameras, assembly of the electrical infrastructure, calibration and integration with the existing management system.

Return on Investment (ROI) ROI analysis evaluates the economic feasibility of each proposed solution by relating annual operational gains to the initial investment required for implementation. The calculation was made using the following formula:

$$\text{ROI (\%)} = \left(\frac{\text{Annual Benefit} - \text{Initial Investment}}{\text{Initial Investment}} \right) \times 100\%$$

The estimated payback period was also considered, calculated as:

$$\text{Payback (years)} = \frac{\text{Initial Investment}}{\text{Annual Benefit}}$$

Annual benefits were estimated based on an operational simulation, and include three main components: (i) savings from reduced operator numbers, (ii) time saved in the replenishment process, (iii) fewer deviations caused by product shortages in channels. The results obtained for each solution are presented in Table 5.4.

Table 5.4: Estimated ROI and Payback Time by Solution

Solution	Investment (€)	Annual Benefit (€)	ROI (%)	Payback (years)
Kardex	603,000	141.670,41	-76,50%	4.25
Wiimer	24,500	42,804.93	74,70%	0.57
Inovesense	550,000	78,769.57	-85.70%	6.98

Reducing the number of Kardex units to only A-turnover products significantly lowers the initial investment while maintaining relevant operational benefits, such as ergonomic improvements, fewer deviations, and improved logistics flow. Freed-up space also enhances operational conditions and productivity, even though this positive impact wasn't directly quantified in the ROI¹.

5.4 Strategic Evaluation Based on Balanced Scorecard

In order to support the final decision on the solution best suited to the company's operational reality, the Balanced Scorecard (BSC) methodology was used, enabling a structured assessment

¹The impact of reduced occupied space, ergonomic improvements, and increased flow efficiency wasn't monetarily quantified due to measurement difficulties, though these are strategically relevant gains

of the alternatives based on multiple strategic perspectives: financial, internal customers, internal processes, learning and growth, and risk/responsibility.

Each criterion was weighted according to its relevance to the logistics operation being analysed. The scores awarded were based on objective data, operational simulations and qualitative analyses carried out in previous work. The detailed description of each criterion can be found in Appendix I. The BSC structure is shown in Figure I.1 of the same Appendix. The weighted average scores for each solution were as follows: Kardex scored 4.12, Wiimer received 3.88, and Inovesense obtained 3.28.

The Kardex solution obtained the highest rating, reflecting its strong performance in the operational, ergonomic and reliability dimensions. Despite the high initial investment, it stands out for its robustness, positive impact on working conditions and potential for structural transformation of the logistics operation.

The Wiimer solution, although with a slightly lower score, has significant advantages in terms of initial investment, speed of implementation and functional scalability. Its integration with existing systems and use of predictive algorithms make it a technically sound and economically viable solution for a first phase of modernisation.

The Inovesense proposal, despite its technological potential, fell short of the others due to its high implementation complexity, total system cost and lower flexibility. Its adoption could be considered in the future, in a context of greater digital maturity and financial capacity.

It can therefore be concluded that the analysis based on the Balanced Scorecard validates Kardex as the solution with the best overall performance, although Wiimer appears to be the most pragmatic alternative for a phased adoption with a quick return on investment.

Chapter 6

Conclusion

The pharmaceutical industry has experienced sustained growth over recent decades, accompanied by increasingly demanding requirements in terms of traceability, reliability, and service speed. In a sector where delivery times are tight, errors can have serious consequences, and product variety is considerable, automation has become a necessity rather than an option. A-Frame systems, particularly effective in handling high-turnover items, are commonly used in pharmaceutical logistics platforms to cope with growing operational pressure. However, despite their efficiency in the picking phase, the overall reliability of these systems still depends heavily on the quality of the replenishment process, which, in practice, has proven to be a critical point of failure.

At Medlog, the logistics operator within the Coopprofar group, the replenishment of A-Frame channels remains largely manual and based on visual assessment by operators. The diagnostic phase revealed that this method, in addition to being highly dependent on individual experience, lacks any structured decision-making logic, such as consumption patterns or product criticality. An analysis of operational data over a one-year period identified a total of 102,052 logistical deviations, 98.7% of which were caused by A-Frame operations. Furthermore, 93% of these deviations were due to stockouts in the A-Frame channels at the moment of picking, with the remaining incidents linked to technical errors.

Replenishment behaviour was also examined according to ABC classification, based on average daily dispatch frequency. Class A items, although representing just 20% of the product base, accounted for 74% of total dispatch volume, underscoring the importance of systematically prioritising these items in replenishment logic. The current practice, however, treated all items equally, regardless of operational impact, resulting in frequent stockouts of critical products and reactive corrective actions.

In parallel, the ergonomic and operational dimensions of the replenishment task were assessed. These included the average task duration, distances covered by operators, and the physical volume of items handled. On average, replenishment took approximately 68 seconds per item, with significant variation depending on category and weight. It was also found that around 33% of products required the handling of medium to large volumes, thereby increasing physical strain on operators and raising the likelihood of errors or delays.

In response to this diagnosis, three intervention strategies were investigated, each with a distinct technological profile and projected operational impact. The first involved replacing the existing dynamic shelving with vertical automated storage modules, enabling structured replenishment by levels. The second strategy introduced a predictive model built on machine learning algorithms, trained using historical consumption data. The third proposed the integration of computer vision systems to monitor stock levels in real time and trigger automatic alerts when thresholds were breached.

All three solutions were tested through discrete-event simulation using the SimPy library in Python. This enabled a rigorous comparison based on key performance indicators, including deviation frequency, replenishment time, physical workload, adaptability, and implementation cost. The vertical storage solution proved the most robust, reducing average daily deviations from 287 to 190 and cutting average replenishment time by 44.10%. The predictive model brought deviations down to 173 per day, with a 28.00% improvement in replenishment time, and offered easy integration with existing systems. Computer vision achieved a reduction to 162 deviations per day and improved replenishment time by 37.50%, but required more complex technical infrastructure and a greater implementation effort.

In conclusion, the multi-criteria analysis using the Balanced Scorecard enabled a comprehensive and structured evaluation of the proposed solutions. The results validate Kardex as the most robust and high-performing option, while also identifying Wiimer as a pragmatic and scalable alternative for phased implementation.

This study set out not only to quantify a specific operational issue, but also to propose integrated, data-driven solutions that reconcile technological efficiency with human factors and existing operational knowledge. Improving replenishment within A-Frame systems proved to be a strategic lever in strengthening overall logistical reliability, with direct implications for service quality and the sustainability of human resources in fast-paced pharmaceutical supply chains.

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Appendix A

MedLog, SA Platform Locations



Figure A.1: Map showing the locations of the logistics platforms

Appendix B

Figures Supporting the Literature Review

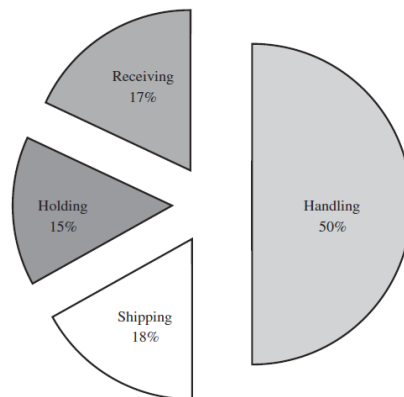


Figure 5.3 Common warehouse costs.

Figure B.1: Warehouse Costs (Rushton et al., 2010)

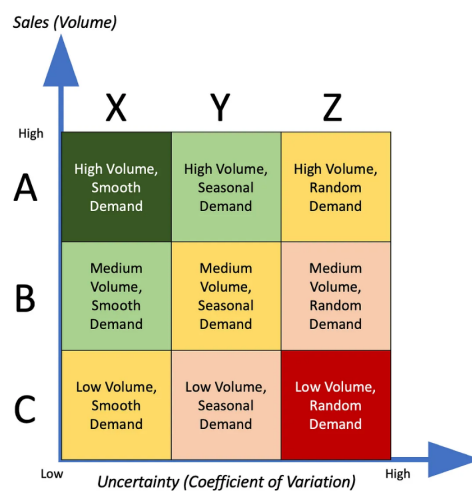


Figure B.2: ABC-XYZ classification matrix (AI, 2023)



Figure B.3: Vertical Lift Modules (VLM) structure (Australia, 2025)

Appendix C

Flowchart of the Logistics Processes

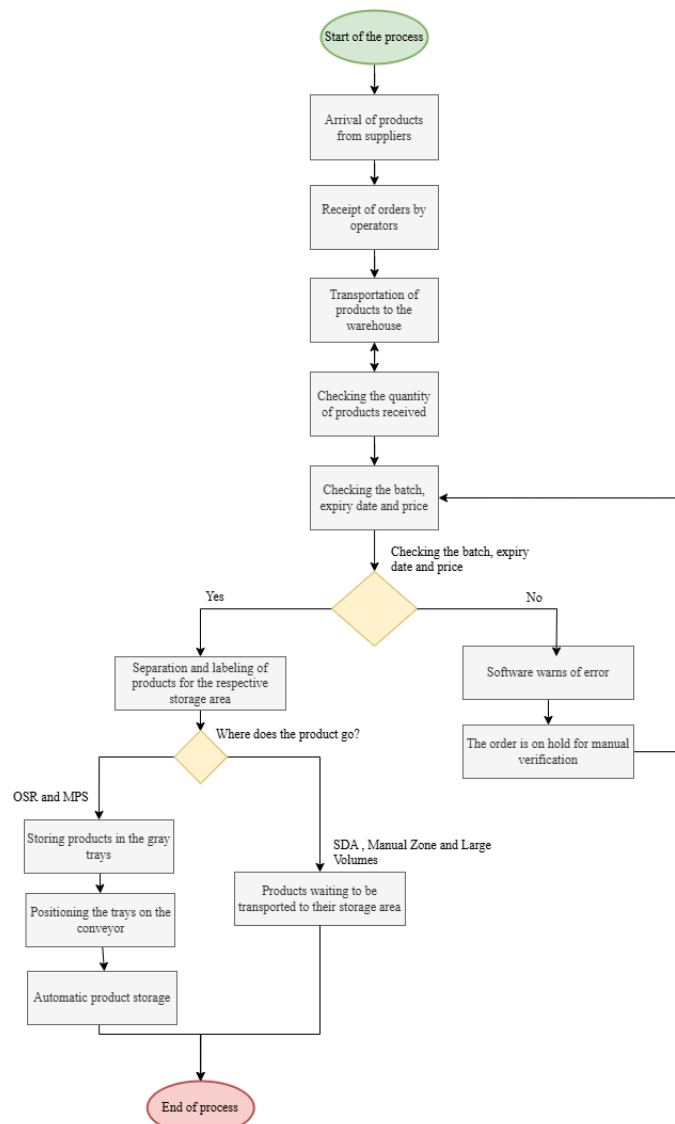


Figure C.1: Flowchart of Reception Process

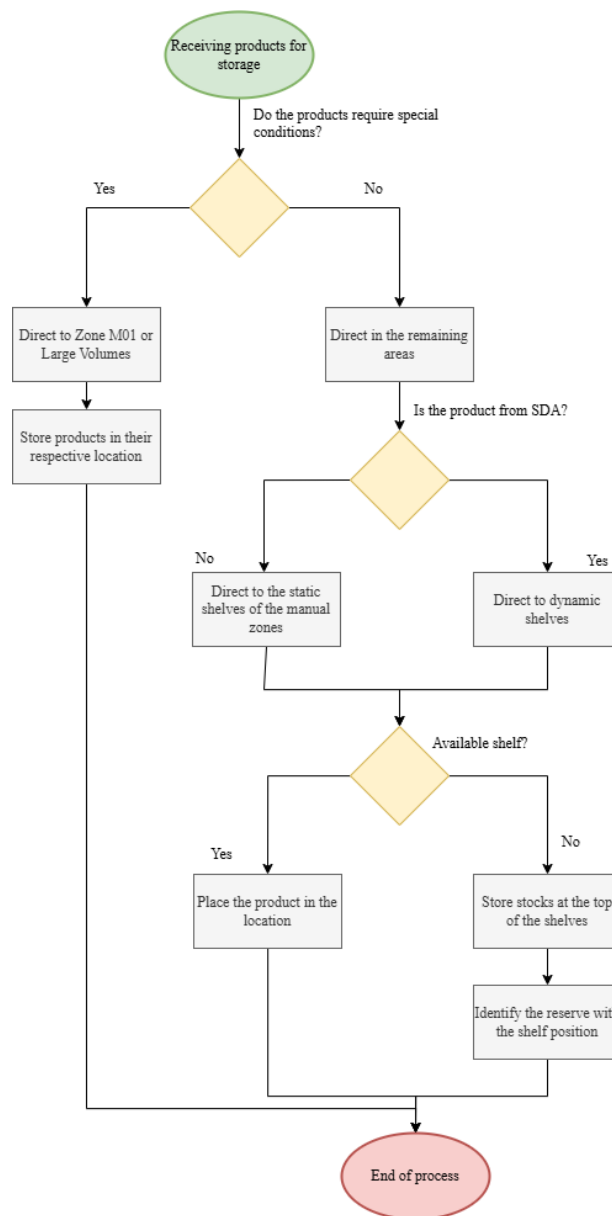


Figure C.2: Flowchart of Storage Process

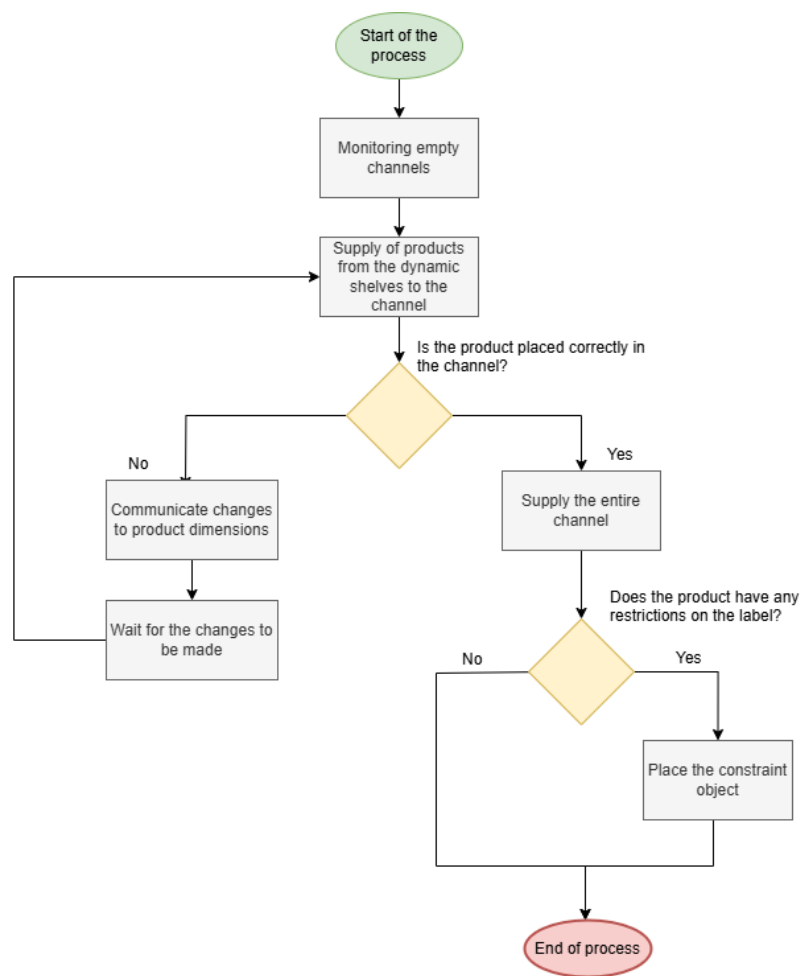


Figure C.3: Flowchart of A-Frames Replenishment Process

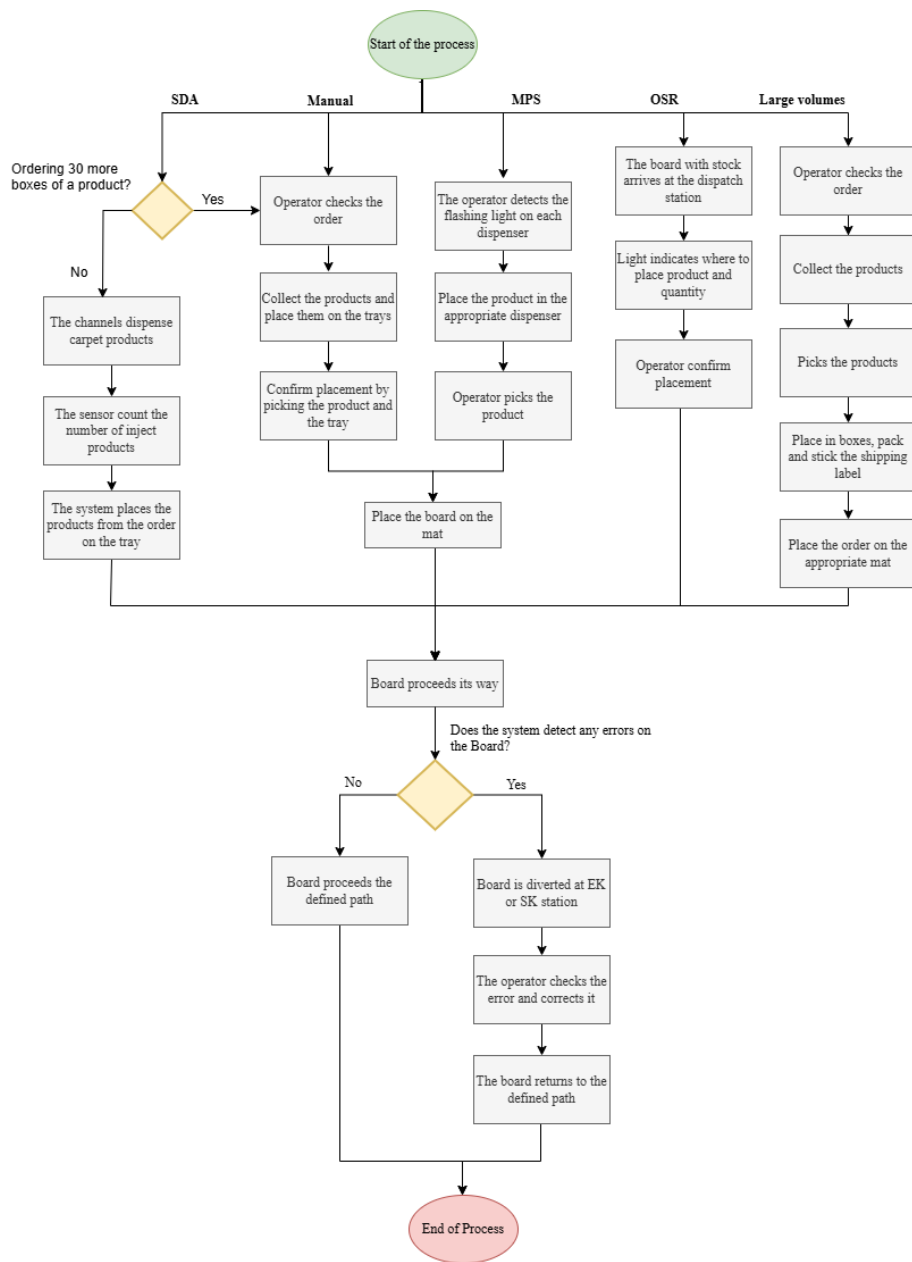


Figure C.4: Flowchart of Picking Process

Relational Data Structure and Operational Analysis Dashboards

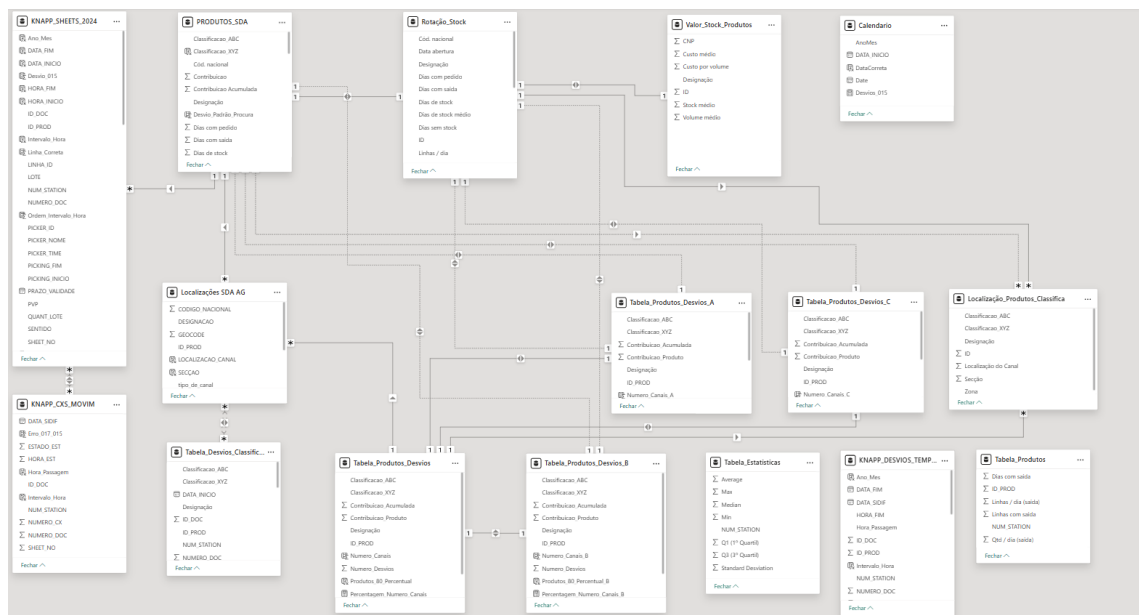


Table D.1: Designation of stations

Station Number	Station Name	Designation
001	M01	Virtual station for manual picking
002	M02	Manual picking station
003	M03	Manual picking station
004	M04	Manual picking station
005	M05	Manual picking station
006	AV01	Order start station
010	AL01	Registration reading station for ABA 1
015	EK01	Final check station
016	M06	Manual picking station
017	SK01	Special check station
018	SK02	Special check station
021	K01	Decision station
022	K03	Decision station
023	K21	Shortcut station to the OSR system
024	K22	Decision station to SK01
025	ABA01	Automatic label insert station
026	RB01	Automatic invoice insert station
027	MD01	Manual lidding
028	DM01	Lidding machine
029	K22A	Virtual station for diversion into M02
031	BD01	Turning device
036	K11	Decision station
051	UE01	Repeat loop station
062	SDA	Central Belt System with ejector type "SDA"
063	SDA2	Central Belt System with ejector type "SDA1"
092	AL02	Announcement Reading station for RB01
100	OSR1	OSR Shuttle Evo
159	SK01 RF	Need for RF Picking
203	OSRDS	OSR-DS

D.1 Detailed explanation of each Dashboard

General analysis of the number of lines and deviations from 2024 The main purpose of the first dashboard, Figure D.2, is to present a clear and structured view of the volume of lines processed in the logistics system throughout 2024, as well as to identify deviations, with special emphasis on the SK season.

Over the period analysed, 11,789,263 lines were processed, with a monthly average of 982,438.58 and a standard deviation of 39,041.50, indicating a relatively stable distribution of monthly data. The total growth rate recorded was -0.42 per cent, reflecting a slight overall drop over the year.

With regard to deviations, 102,052 occurrences were recorded at the SK station, representing just 0.87 per cent of the total number of lines processed. This proportion is visibly reduced, as illustrated in the circular graph, which highlights that more than 99 per cent of lines had no deviations at all.

The dashboard also allows a detailed analysis by station, showing that stations 062, 100 and 063 are responsible for the greatest volume of processing. Despite this operational load, the number of deviations at these stations remains low, which demonstrates good process performance and reliability.



Figure D.2: General analysis of the number of lines and deviations from 2024

Global analysis of deviations at SK and EK diversion stations The second dashboard, Figure D.3, presents a detailed analysis of the occurrences of deviations at SK station, with the aim of understanding their distribution over time, identifying the causes and assessing the incidence by station.

Over the course of 2024, 102,052 deviations were recorded. The vast majority were due to product shortages, accounting for 96,644 cases, or 94.7 per cent of the total. The remaining 5,408 deviations (5.3 per cent) are associated with technical errors, as illustrated in the distribution chart of deviation types.

The monthly visualisation shows that although the total number of lines processed per month remains relatively stable, the number of deviations shows significant peaks, especially in March, May and November. The monthly percentage rate follows this trend, reaching its highest value in May, with a rate of approximately 1.01

Finally, the analysis by station shows that station 062 concentrates the majority of deviations, with 68,249 due to product shortages and 7,088 due to technical errors. Relevant figures are also evident at station 063, with 28,395 and 2,965 deviations respectively.

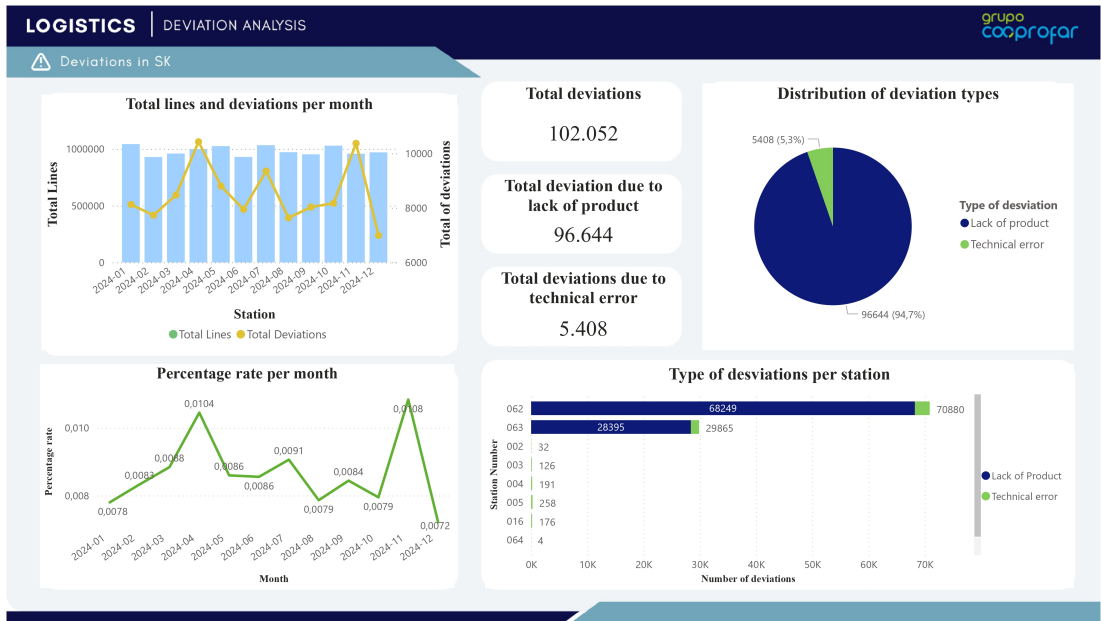


Figure D.3: Global analysis of deviations at SK and EK diversion stations

Analysing the type of deviations in SK by month and hourly interval This dashboard, Figure D.4 focuses on characterising the deviations recorded at the SK station, detailing their monthly and hourly average, as well as the origin of these deviations over time.

Throughout 2024, there was an average of 8,504.33 deviations per month, with a standard deviation of 1,017.04, which indicates some variability between months. In hourly terms, the average number of deviations per hour is 4,252.17, with the majority of these cases being associated with product shortages (3,993.96), in contrast to the 258.21 deviations per hour resulting from technical errors.

The monthly analysis shows that although both types of deviations are present throughout the year, the highest values occur in April, November and July, with a particularly high number of failures related to product shortages. Even so, technical errors remain significantly lower in all months.

The hourly distribution of deviations reveals interesting patterns. Between 7am and 9am, as well as between 9pm and 2am, there is a marked increase in the total number of deviations, especially those related to product shortages. These peaks may indicate critical moments in the process, requiring attention to stock management and supply at specific times.

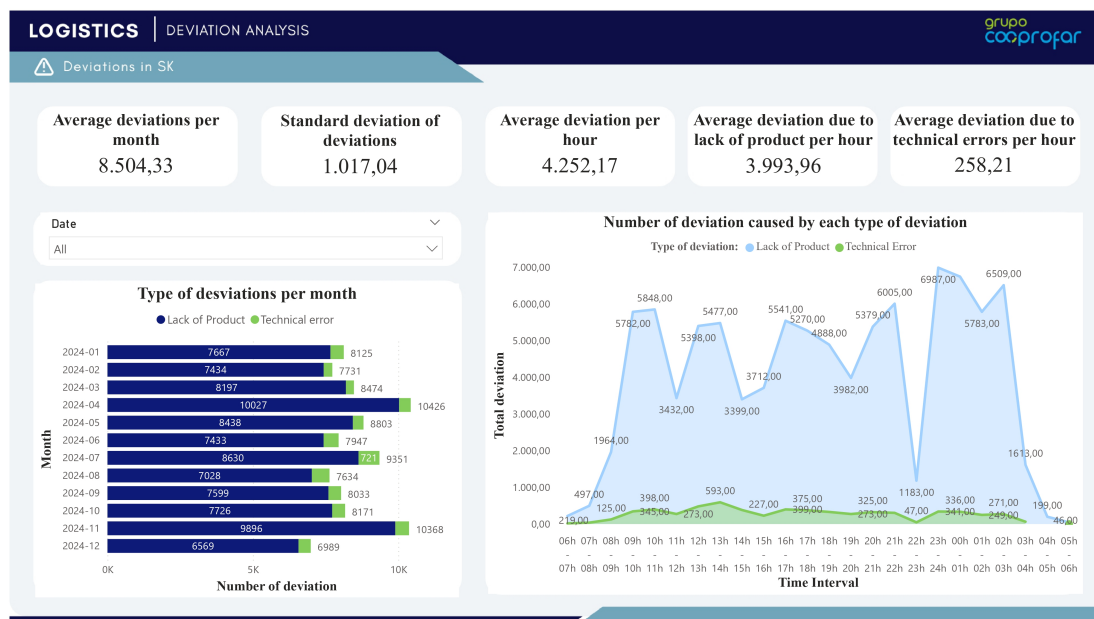


Figure D.4: Analysing the type of deviations in SK by month and hourly interval

General Analysis of A-Frame Deviations This dashboard in Figure D.5 focuses on analysing the deviations recorded in the SDA, with an approach that combines the monthly volume of occurrences with their detailed distribution by type and location.

During 2024, 100,745 SDA deviations were identified, which represents 1.28% of all lines processed. The overwhelming majority of these deviations are related to product shortages, totalling 96,644 cases, while technical errors account for 4,101 deviations, remaining a residual cause.

The monthly analysis shows that the months with the highest number of occurrences were April, November and July, highlighting the constant prevalence of product shortages as the main cause throughout the period. This pattern is reinforced by the bar chart, where the dark blue colour clearly predominates over the green (technical error).

The dashboard also includes a monthly heat map detailing the distribution of deviations by day and month. This visualisation makes it possible to identify the periods of greatest incidence, for example, in June and November, deviations are concentrated more intensely between the 6th and 13th, suggesting operational peaks or recurring failures in this interval. The granularity of this matrix makes it easier to detect critical patterns in the logistics calendar, useful for more precise corrective actions.

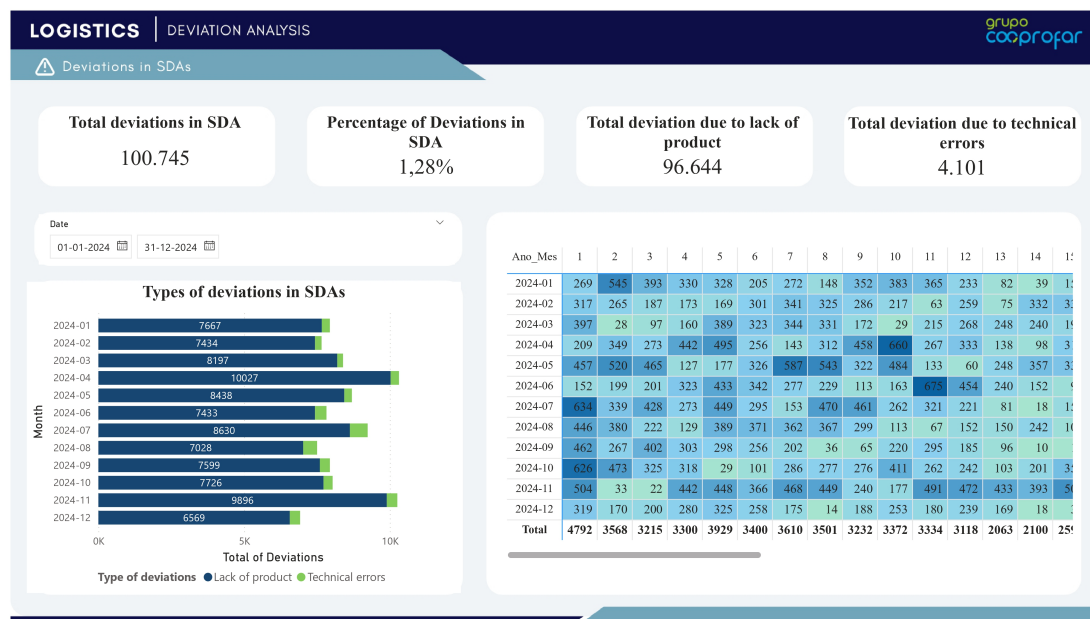


Figure D.5: General Analysis of A-Frame Deviations

Dashboard with analysis of total deviations and SDA averages by interval This visualisation of the Figure D.6 focuses on a detailed analysis of the deviations recorded in the SDAs throughout the day, paying special attention to the average number of deviations per hour and the average duration associated with each type of occurrence.

The overall average number of deviations per hour is 4,197.71, most of which correspond to failures due to lack of product (4,026.83), while technical errors account for just 186.41 cases per hour. This distribution is also evident in the bottom left-hand graph, where peaks of occurrences can be seen between 10am and 1pm and between 9pm and 2am, with a maximum of 7,189 deviations recorded between 1am and 2am.

The graph on the right shows the average duration of deviations by type. Deviations due to lack of product have a longer impact on operating time, with values reaching 29.20 minutes in the 02h-03h period. On the other hand, deviations due to technical errors are almost always below 2 minutes, with residual variations across the different time slots.

In general, the data shows that, as well as being more frequent, deviations due to lack of product represent greater operational disruption, especially during critical periods of the daily cycle.



Figure D.6: Dashboard with analysis of total deviations and SDA averages by interval

Dashboard with A-Frame deviation correction time The purpose of the analysis shown in the Figure D.7 is to analyse the average times taken to correct deviations in the A-Frame, broken down by time of day and divided into product shortages and technical errors.

The correction time corresponds to the interval between the moment the tray is diverted because it has an anomaly and the moment it returns to the conveyor with the appropriate correction made. On average, this time is 39.89 minutes per hour. In the case of deviations due to lack of product, the average time is 39.68 minutes, while technical errors have a slightly higher value of 46.48 minutes, which may indicate greater complexity or the need for longer manual intervention.

The graph on the left shows that the highest times occur between 9pm and 11pm, with a peak of 60 minutes. Other intervals with high times are between 7am and 9am and between 11pm and 1am, which may indicate times of greater operational pressure or limited resources.

The graph on the right shows the comparison by type of deviation. Consistently, technical errors tend to have longer correction times than product shortages, especially at the end of the day and in the early hours of the morning.

This analysis makes it possible to identify the most critical periods in terms of response time and can be useful for improving team management and the distribution of resources throughout the day.

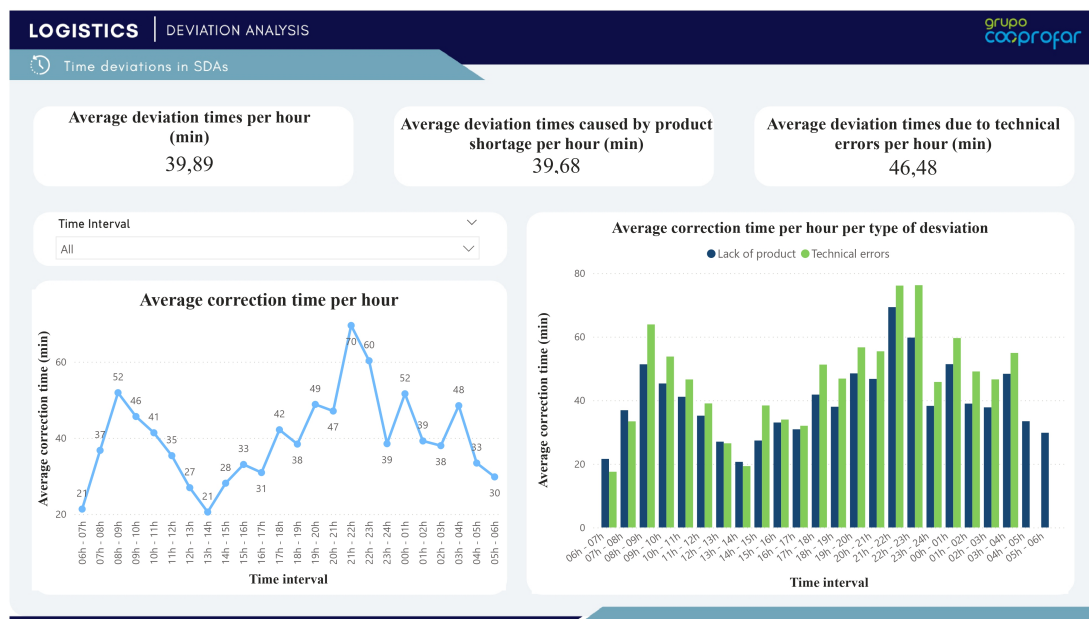


Figure D.7: Dashboard with A-Frame deviation correction time

ABC/XYZ analysis of A-Frame products This panel in the Figure D.8 shows an ABC analysis of the products in stock, based on the total volume of units sold in 2024 and their monthly distribution.

During the year, 28,124,024 products were sold, with a total of 1,734 references currently in stock. The product analysed in this dashboard is classified as category A in the ABC analysis, which means it represents a significant part of the sales volume. At the same time, in the XYZ classification, it is identified as type X, indicating constant and predictable demand over time.

The circular graph shows the distribution of products in stock by ABC category:

- 50% of the products belong to category B (867 units),
- 29.99% to category C (520 units),
- 20.01% to category A (347 units).

Although category A represents a smaller number of products, they are the most important in terms of sales volume.

The line graph on the right shows the distribution of monthly demand throughout 2024. There is some slight oscillation between the months, with figures varying between 2.2 and 2.6 million units sold, but overall a stable demand trend is maintained throughout the year.

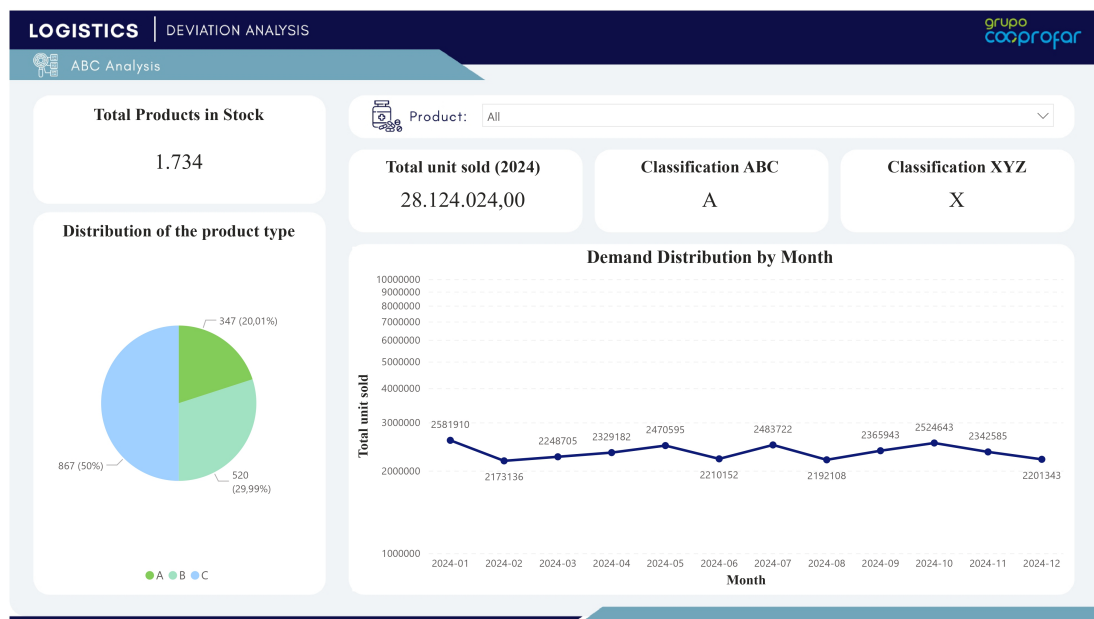


Figure D.8: ABC/XYZ analysis of A-Frame products

Dashboard of A-Frame products with the greatest deviation and their ABC/XYZ classification This panel in the Figure D.9 cross-references the information from the ABC and XYZ classifications with the deviations recorded throughout 2024, allowing us to identify which products have the greatest impact on logistical failures.

In total, 97,439 deviations were recorded, with the vast majority (93,487) due to product shortages and only 3,952 associated with technical errors. The list of products on the left shows the designation, the respective classifications and the total number of deviations. It can be seen that products classified as A-Y (i.e. very relevant in terms of sales and with stable demand) have a high number of occurrences, such as Inderal 10 mg with 578 deviations.

For example, the product Bisoprolol Aurobindo 2.5mg, classified A-Z, which despite having irregular demand, accumulated 362 deviations - which may represent a greater risk for stock control.

On the right-hand side, the heat map shows the distribution of deviations by month and by product, making it possible to identify temporal patterns. A more pronounced concentration can be seen in the months of October and November, particularly for the items in columns 6, 10 and 12, which recorded consistently high values.

This type of visualisation is useful for supporting more informed operational decisions, particularly in terms of product replenishment, inventory control and demand forecasts.

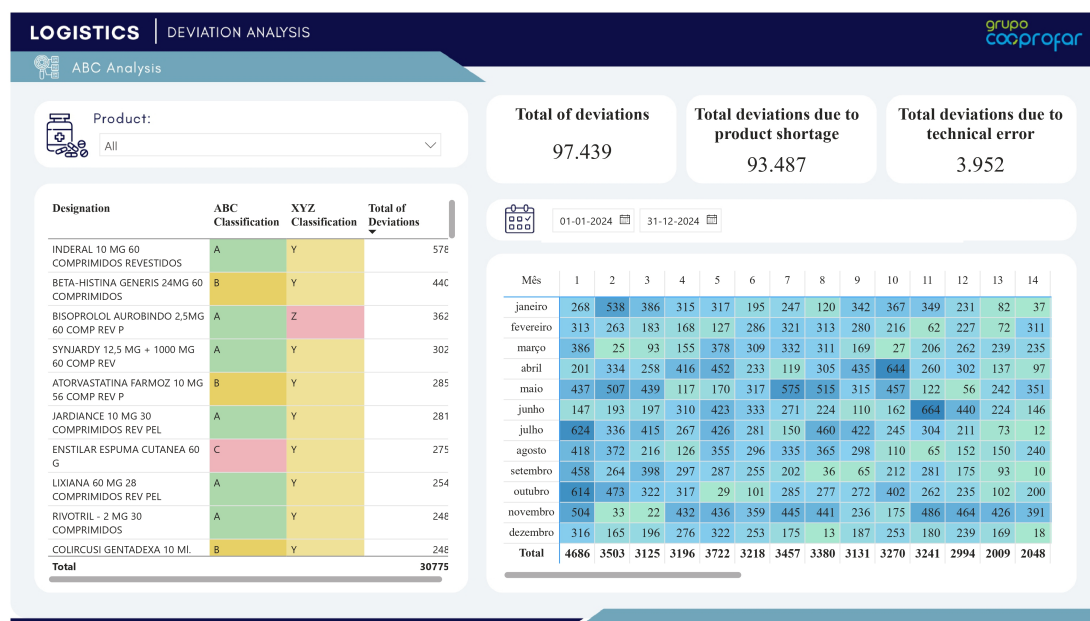


Figure D.9: Dashboard of A-Frame products with the greatest deviation and their ABC/XYZ classification

Dashboard of the 20% of A-Frame products that cause 80% of deviations Finally, the dashboard in the Figure D.10 shows an analysis of the distribution of deviations by ABC classification, with the aim of identifying the most critical products and channels, responsible for a significant proportion of the occurrences.

Of the total number of deviations, 47.84 per cent occurred in class A products, 31.32 per cent in class B products and 20.84 per cent in class C products. The bar chart confirms that class A has the highest absolute volume of deviations, with more than 46,000 occurrences, which reflects the operational impact of failures in products with greater commercial relevance.

In total, 1,571 products were identified, accounting for 80 per cent of the errors recorded. The distribution of these products by category shows that 47.99 per cent belong to class C, 30.62 per cent to class B and 21.39 per cent to class A, which indicates that although class A has more deviations in absolute value, class C makes a significant contribution when looking only at the most critical group.

In addition, the data shows that only 30.43% of the channels were responsible for 80% of the occurrences of deviations, suggesting that a small part of the system concentrates most of the problems - which can help to prioritise intervention.

The table in the bottom right-hand corner lists the products with the greatest deviations, accompanied by their ABC and XYZ classifications.

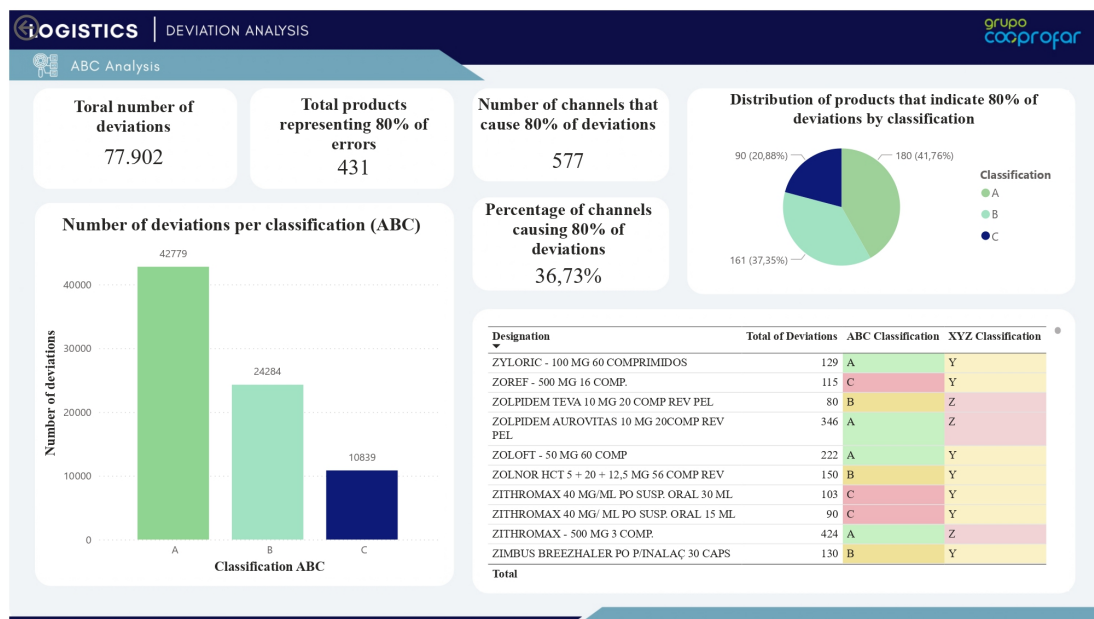


Figure D.10: Dashboard of the 20% of A-Frame products that cause 80% of deviations

Appendix E

Python Code for ABC and XYZ Classification

The following Python code performs the ABC and XYZ classification for the product dataset.

Listing E.1: Python Code for ABC and XYZ Classification

```
1  import pandas as pd
2  import numpy as np
3  from scipy.stats import entropy
4  from scipy.spatial.distance import euclidean
5  from pulp import LpMinimize, LpProblem, LpVariable
6
7  # Load data
8  df = pd.read_excel("Prod_SDA.xlsx")
9
10 # Remove empty rows
11 df.dropna(how="all", inplace=True)
12
13 # Display the first rows to check
14 print(df.head())
15
16 # 1. Select only numeric columns for analysis
17 df_numeric = df.select_dtypes(include=[np.number])
18
19 # Check the types of the numeric columns
20 print(df_numeric.dtypes)
21
22 # 2. Normalize the data
23 df_normalized = (df_numeric - df_numeric.min()) / (df_numeric.max() -
24             df_numeric.min())
25
26 # 3. Calculate the weights using Shannon's Entropy
27 P = df_normalized / df_normalized.sum(axis=0)
28 entropy_values = -np.nansum(P * np.log(P), axis=0)
29 weights = (1 - entropy_values) / np.sum(1 - entropy_values)
30
31 # Create a dictionary with the weights
32 weights_dict = dict(zip(df_numeric.columns, weights))
33 print("Criterion weights:", weights_dict)
34
35 # 4. Apply TOPSIS to classify the products
36 positive_ideal = df_normalized.max()
37 negative_ideal = df_normalized.min()
```

```

37
38 # Calculate the Euclidean distances from the ideal and negative solutions
39 dist_pos = np.sqrt(((df_normalized - positive_ideal) ** 2).sum(axis=1))
40 dist_neg = np.sqrt(((df_normalized - negative_ideal) ** 2).sum(axis=1))
41
42 # Calculate the TOPSIS score and classify the products
43 df["TOPSIS Score"] = dist_neg / (dist_pos + dist_neg)
44
45 # To avoid duplication, add a small noise to the TOPSIS score
46 df["TOPSIS Score"] += np.random.uniform(0, 1e-6, size=len(df)) # Small noise
47
48 # Calculate the ranking based on the TOPSIS score
49 df["Ranking"] = df["TOPSIS Score"].rank(ascending=False)
50
51 # 5. Apply Goal Programming for ABC Classification
52 model = LpProblem("ABC_Classification", LpMinimize)
53 A = LpVariable("A", lowBound=0, cat='Integer')
54 B = LpVariable("B", lowBound=0, cat='Integer')
55 C = LpVariable("C", lowBound=0, cat='Integer')
56
57 # Constraints to follow the Pareto rule
58 model += A + B + C == len(df) # All products must be classified
59 model += A <= 0.2 * len(df) # Class A up to 20% of products
60 model += B <= 0.3 * len(df) # Class B up to 30% of products
61 model += C >= 0.5 * len(df) # Class C at least 50% of products
62
63 # Solve the optimization problem
64 model.solve()
65 print(f"Class A: {A.varValue} products")
66 print(f"Class B: {B.varValue} products")
67 print(f"Class C: {C.varValue} products")
68
69 # 6. Apply ABC classification to the products
70 df["ABC Classification"] = "C" # Initially classify all as C
71 df.loc[df["Ranking"] <= A.varValue, "ABC Classification"] = "A"
72 df.loc[(df["Ranking"] > A.varValue) & (df["Ranking"] <= A.varValue +
73     B.varValue), "ABC Classification"] = "B"
74
75 # 7. Calculate the cumulative 80% of movement (based on daily sales quantity)
76 df['Daily Movement'] = df['Qtd / dia (saida)'] # Removido acento
77
78 # Sort the products by daily movement, from highest to lowest
79 df = df.sort_values(by='Daily Movement', ascending=False)
80
81 # Calculate the total movement value
82 total_movement = df['Daily Movement'].sum()
83
84 # 1. Calculate the Contribution of each product
85 df['Contribution'] = df['Daily Movement'] / total_movement
86
87 # 2. Calculate the Cumulative Contribution
88 df['Cumulative Contribution'] = df['Contribution'].cumsum()
89
90 # Display some of the first rows to check
91 print(df[['ID', 'Designation', 'Qtd / dia (saida)', 'Contribution',
92     'Cumulative Contribution']].head())
93
94 # If you want to save the solution to an Excel file
95 df.to_excel("Classification_with_Contribution.xlsx", index=False)

```

```
95     # Display some of the first rows of the result to check
96     print(df.head())
```


Appendix F

Additional Details on the Proposed Solutions

Solution 1: Using a Kardex Vertical Carousel Module



Figure F.1: Details of the Kardex VCM touch console

Solution 2: Application of Artificial Intelligence Algorithms

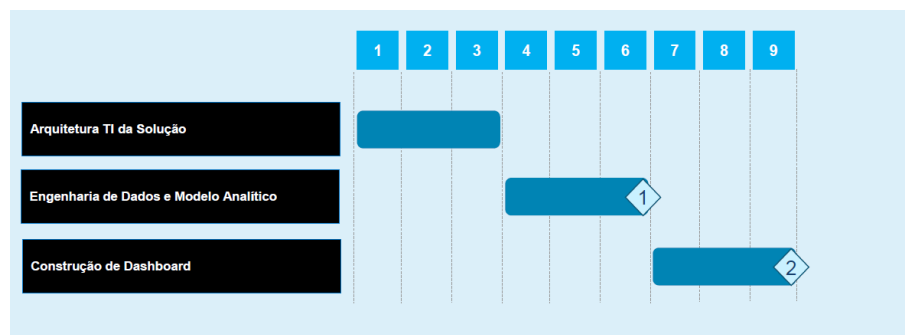


Figure F.2: Wiimer project timeline

Appendix G

Simulation Configuration and Code

Table G.1: Data files used in the simulation

File Name	Format	Description
Dados_simulacao	Excel (.xlsx)	Core product data: designation, ABC classification, zone, channel location, daily movement estimates, and activation probabilities.
Dados_canaais	Excel (.xlsx)	Channel characteristics per product: number of channels, units per channel, maximum stock, channel type (large/small), and replenishment frequency.
Linhas_SDA	Excel (.xlsx)	Number of lines processed per day in 2024, used to estimate average daily order volume.
Medias_desvios_2024	Excel (.xlsx)	Average hourly technical deviation rates, applied even when stock is available.
Medias_tempos_hora	Excel (.xlsx)	Average correction time for deviated trays, used in the simulation of technical error handling.

Table G.2: Variables used in the simulation

Variable	Type	Description
Designation	String	Product identifier or name
Qtd.canaais	Integer	Number of dedicated channels for the product
Units per channel	Integer	Maximum storage units allowed per channel
Maximum Quantity	Integer	Total system capacity for that product
Daily Movement	Integer	Estimated daily demand
requests	Accumulator	Total units requested throughout the simulation
sim_deviations	Accumulator	Total deviations (technical or due to stockouts)
times_empty	Accumulator	Number of times a channel was depleted
times_replenished	Accumulator	Number of replenishment events
wait_time	Minutes	Cumulative waiting time until stock replenishment

Python Code The following Python code performs the Simpy code of simulation.

Listing G.1: Full Python Simulation Code with Scenario Logic

```

1 # === INSTALL REQUIRED PACKAGES ===
2 !pip install simpy pandas openpyxl matplotlib seaborn --quiet
3
4 # === IMPORT MODULES ===
5 import simpy
6 import pandas as pd
7 import numpy as np
8 import random
9 import os
10 from datetime import datetime
11 import matplotlib.pyplot as plt
12 import seaborn as sns
13
14 # === SCENARIO SELECTION: choose between 'original', 'kardex', 'camara', or
15   'algoritmo' ===
16
17 cenario = "original"
18
19 # === MOUNT GOOGLE DRIVE AND DEFINE PATHS ===
20 from google.colab import drive
21 drive.mount('/content/drive')
22 base_path = "/content/drive/MyDrive/Simulacao"
23 data_path = os.path.join(base_path, "data")
24 output_path = os.path.join(base_path, "output")
25 os.makedirs(output_path, exist_ok=True)
26
27 # === LOAD DATASETS ===
28 df_base = pd.read_excel(os.path.join(data_path, "Dados_para_simulacao.xlsx"))
29 df_repos = pd.read_excel(os.path.join(data_path, "Dados_canais_simulacao.xlsx"))
30 df_linhas = pd.read_excel(os.path.join(data_path, "Linhas_feitas_SDA.xlsx"))
31 df_desvios = pd.read_excel(os.path.join(data_path, "Medias_desvios_2024.xlsx"))
32 df_tempos = pd.read_excel(os.path.join(data_path, "Medias_tempos_hora.xlsx"))
33
34 # === DATA PREPROCESSING ===
35 df = pd.merge(
36     df_base[["Designacao", "Classificacao_ABC", "Zona", "SECCAO",
37             "LOCALIZACAO_CANAL", "Movimentacao Diaria"]],
38     df_repos[["Designacao", "Qtd. canais", "Unidades por canal",
39             "Quantidade_Maxima", "Dias_reposicao"]],
40     on="Designacao", how="left"
41 ).dropna(subset=["Qtd. canais"])
42
43 df["stock_total"] = (df["Quantidade_Maxima"] * 0.6).astype(int)
44 df["capacidade_canal"] = df["Unidades por canal"].astype(int)
45
46 for col in ["pedidos", "desvios_simulados", "vezes_vazio", "vezes_reposto",
47            "tempo_espera_reposicao"]:
48     df[col] = 0
49
50 df_desvios["Hora"] =
51     df_desvios["Intervalo_Hora"].astype(str).str.extract(r"(\d+)").astype(float).fillna(-1).astype(int)
52 df_desvios["Mes"] = df_desvios["Mes"].str.lower()
53 desvio_dict = df_desvios.set_index(["Mes", "Hora"])["Media_Desvios"].to_dict()
54
55 df_linhas["chave"] = df_linhas["Mes"].str.lower() + "-" +
56     df_linhas["Dia"].astype(str)
57 media_linhas_dict = df_linhas.set_index("chave")["Total_Linhas"].to_dict()
58
59

```



```

52 produto_para_canais = df.groupby("Designacao", group_keys=False).apply(lambda d:
    d.index.tolist()).to_dict()
53
54 # === SIMULATION PARAMETERS ===
55 MINUTOS_DIA = 1440
56 DIAS = 365
57 TOTAL_MINUTOS = DIAS * MINUTOS_DIA
58 lista_meses = ["janeiro", "fevereiro", "marco", "abril", "maio", "junho",
59               "julho", "agosto", "setembro", "outubro", "novembro", "dezembro"]
60
61 registo_diario = {
62     "Dia": [], "Mes": [], "Pedidos": [], "Desvios": [], "Reposicoes": [],
63     "Total Tempo Reposicao": [], "Operadores Ativos (Media)": []
64 }
65
66 def operadores_por_hora(h):
67     if 9 <= h < 11: return 7
68     elif 11 <= h < 15: return 2
69     elif 15 <= h < 16: return 0
70     elif 16 <= h < 18: return 3
71     elif 18 <= h < 24: return 1
72     elif 0 <= h < 3: return 1
73     return 0
74
75 pesos_horarios = {h: 1.5 if 11.5 <= h < 14.5 or 20 <= h < 24 else 0.5 if 3 <= h <
    7 else 1.0 for h in range(24)}
76
77 def peso_da_hora(h):
78     return pesos_horarios.get(h, 1.0)
79
80 # === MAIN SIMULATION FUNCTION ===
81 def simular():
82     env = simpy.Environment()
83     operadores = simpy.Container(env, init=9, capacity=9)
84     operadores_log = []
85
86     def turnos():
87         while True:
88             h = (env.now % MINUTOS_DIA) // 60
89             ativos = operadores_por_hora(h)
90             diff = ativos - operadores.level
91             if diff > 0: yield operadores.put(diff)
92             elif diff < 0: yield operadores.get(abs(diff))
93             operadores_log.append(operadores.level)
94             yield env.timeout(30)
95
96     def progresso():
97         while True:
98             yield env.timeout(MINUTOS_DIA)
99             d = int(env.now // MINUTOS_DIA)
100             mes = lista_meses[d % 12]
101             registo_diario["Dia"].append(d + 1)
102             registo_diario["Mes"].append(mes)
103             registo_diario["Pedidos"].append(df["pedidos"].sum())
104             registo_diario["Desvios"].append(df["desvios_simulados"].sum())
105             registo_diario["Reposicoes"].append(df["vezes_reposto"].sum())
106             registo_diario["Total Tempo
                Reposicao"].append(df["tempo_espera_reposicao"].sum())
107             registo_diario["Operadores Ativos
                (Media)"].append(np.mean(operadores_log[-48:]))

```

```

108
109 def processo(produto):
110     canais = produto_para_canais[produto]
111     row = df.loc[canais[0]]
112     canais_n = int(row['Qtd. canais'])
113     capacidade = int(row['capacidade_canal'])
114     stock = [int(row['stock_total']) // canais_n] * canais_n
115
116     while True:
117         yield env.timeout(10)
118         h = (env.now % MINUTOS_DIA) // 60
119         d = int(env.now // MINUTOS_DIA)
120         mes = lista_meses[d % 12]
121         chave = f"{mes}-{d+1}"
122         linhas_dia = media_linhas_dict.get(chave, 10000)
123         base_prob = linhas_dia / 1440
124         prob = base_prob * peso_da_hora(h)
125
126         if random.random() < prob:
127             unidades_totais = random.randint(1, 30)
128             df.loc[canais, "pedidos"] += unidades_totais
129
130             if sum(stock) >= unidades_totais:
131                 restantes = unidades_totais
132                 for i in range(canais_n):
133                     if restantes == 0: break
134                     retirar = min(restantes, stock[i])
135                     stock[i] -= retirar
136                     restantes -= retirar
137                 if random.random() < (desvio_dict.get((mes, h), 0) / 100):
138                     df.loc[random.choice(canais), "desvios_simulados"] += 1
139             else:
140                 for canal in canais:
141                     df.loc[canal, "desvios_simulados"] += 1
142                     df.loc[canal, "vezes_vazio"] += 1
143                 if operadores.level > 0 and (cenario != "camara" or
144                     random.random() < 0.9):
145                     yield operadores.get(1)
146                     # === SCENARIO-BASED REPLENISHMENT TIME ===
147                     if cenario == "kardex":
148                         tempo = random.randint(60, 150)
149                     elif cenario == "camara":
150                         tempo = random.randint(120, 300) * 0.7
151                     elif cenario == "algoritmo":
152                         tempo = random.randint(100, 200) if row['Movimentacao
153                             Diaria'] > 200 else random.randint(200, 300)
154                     else:
155                         tempo = random.randint(120, 300)
156                     yield env.timeout(tempo)
157                     stock = [capacidade] * canais_n
158                     for canal in canais:
159                         df.loc[canal, "vezes_reposto"] += 1
160                         df.loc[canal, "tempo_espera_reposicao"] += tempo
161                     yield operadores.put(1)
162
163     env.process(turnos())
164     env.process(progresso())
165     for produto in produto_para_canais:
166         env.process(processo(produto))
167     env.run(until=TOTAL_MINUTOS)

```

```
166
167     # === EXPORT OUTPUT FILES ===
168     kpi_df = pd.DataFrame(registo_diario)
169     df_resultados = df.copy()
170     df_resultados["%_desvios"] = (df_resultados["desvios_simulados"] /
171                                   df_resultados["pedidos"].replace(0, 1)) * 100
171     kpi_df.to_excel(os.path.join(output_path, "KPIs_Diarios.xlsx"), index=False)
172     df_resultados.to_excel(os.path.join(output_path, "KPIs_Canais.xlsx"),
173                            index=False)
173     print("Simulation completed and files exported.")
174
175     # === EXECUTE SIMULATION ===
176     simular()
```


Appendix H

Detailed Data from the Financial and Operational Analysis

H.1 Details of the Operational Analysis

Details of the Kardex solution

ID	Cód. Nacional	Designação	Qtd. Dia. Salda	Dias. Pedir	Custo. Médio	EOQ	SafetyStock	ROP
154237		INCLUI PULVER FARMACE 5 MG/20 COMPRESSOES	45,38738255	180	2744,240111	37	386	8803
14055	859813	ACTIFED 20 COMPRESSOES	30,27927926	180	36307,701111	35	133	3887
20366	281922	ACTIVELLE 1 MG + 0,5 MG 28 COMP REV	34,2375913	180	2823,843796	35	85	2766
133233	708090	ACTIVELLE 40 CAPSULAS	80,27368423	180	37031,81744	27	274	31726
145752	788342	ADALAT CR 10 MG 28 COMPRESSOES LP	50,62765957	180	2882,470222	59	230	9849
133436	5112818	ADONIS-BC 40 MG 28 COMPRESSOES	50,84328884	180	7747,3664	27	340	6000
35059	907868	ADT 10 MG 40 COMPRESSOES REVESTIDOS	52,44975745	180	2388,345111	66	239	33204
35057	907863	ADT 25 MG 40 COMPRESSOES REVESTIDOS	83,1344086	180	3328,86078	30	287	32283
31675	383090	AERONAS NASAL 100 MCG 200 DORES	50,77358491	180	35214,76156	25	231	9878
108603	6191288	AGULHAS B D MICRO FINE 5 MM X 100 SRS	16,88764045	180	3325,798889	52	77	3286
128028	7755504	ADNARA 30 CR	12,84736842	180	5394,355778	23	58	2499
14083	9046755	ALDACTONE 25 MG 40 COMP	48,03157895	180	8765,766667	32	238	9344
2852	2365791	ALOPURINOL RATIOPHARM 100 MG 50 COMP	31,92833759	180	2759,053556	46	145	4211
20905	2584282	ALPRAZOLAM MYLAN 0,5 MG 40 COMPRESSOES	95,89389189	180	6325,346778	53	436	38655
20903	2584480	ALPRAZOLAM MYLAN 1 MG 40 COMPRESSOES	87,05333949	180	8713,850556	43	386	34936
143480	5763867	ALTONIDE 5 MG + 8 MG 28 CAPSULAS	39,3027027	180	3703,695111	46	91	3873
35686	9276147	ANAPRANIL 25 MG 40 COMPRESSOES REVEST	34,13788474	180	477,7708889	74	64	2754
37438	9627814	ANAPRANIL 75 MG 40 COMPRESSOES LP	33,39444444	180	3395,077867	42	61	2686
122648	9607512	ANORO 55 + 22 MCG PO F INALAC 30 DORES	22,97349428	180	11742,871	19	334	4469
147825	9618711	ANTIGRIPPINE TRIDIFFECT TONIC 16 CAPSULAS	50,98943789	180	25167,68256	19	232	9620
27864	4511489	APOCARD 100 MG 40 COMP	13,74498722	180	4036,082556	25	63	2674
38846	9524215	ARCOLARON 200 MG 40 COMP	23,3	180	6449,501111	25	97	4144
18113	9876115	ASP 100 MG 40 COMPRESSOES	38,72282699	180	3843,997111	40	176	7833
14375	8453300	ASPRONA-C 10 COMP	10,5178847	180	9674,113	18	48	2046
40589	5475397	ATARAX 25 MG 20 COMP	21,50549493	180	3033,563222	62	98	4384
155126	7852264	ATROBEX 20 MG + 10 MG 30 CAPSULAS	19,93525466	180	4387,132444	29	93	3876
155187	7888860	ATROBEXATINA PHARMAGEN 20 MG 30 COMP	20,87368423	180	11750,36256	18	95	4082

Figure H.1: Calculation of EOQ, ROP and Safety Stock for Pharmaceutical Products

Technical Specifications – Kardex System The Kardex Megamat 350 is a high-density vertical storage system designed for automated stock management and ergonomic product handling. Its structure consists of rotating trays (shelves) that circulate vertically within a metal enclosure, allowing operators to access stored items at an ideal working height.

The module proposed for this project was selected based on the available vertical clearance and operational requirements of the company's warehouse. Its key technical specifications are as follows:

- **Total unit height (external):** 7,100 mm
- **Useful internal height:** 6,410 mm
- **Number of shelves per module:** 24
- **Shelf dimensions:** 2,850 mm (width) × 626 mm (depth) × 407 mm (height)
- **Maximum load per shelf:** 350 kg
- **Floor area occupied per module:** 5.8 m²
- **Total useful storage volume per module:** 37.22 m³

- **Estimated total storage capacity:** up to 168 boxes (each 400 × 600 × 350 mm)

These specifications enable a compact yet highly efficient vertical storage solution, capable of significantly reducing the footprint required compared to traditional dynamic shelving systems.

Figure H.2 presents the full external dimensions of the Kardex Megamat 350 module, including height, width, and base area. Figure H.3 shows a detailed view of an individual shelf and its internal configuration.

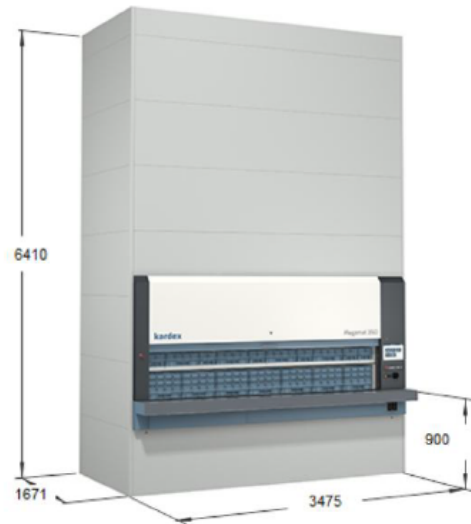


Figure H.2: Detail of the dimensions of the Kardex VCM



Figure H.3: Detail of kardex shelf dimensions

Table H.1: NIOSH Parameter Comparison – Current Situation vs Kardex Solution

Parameter	Current Situation	With Kardex
Lifting height (<i>VM</i>)	180 cm	100 cm
Horizontal distance (<i>HM</i>)	35 cm	20 cm
Frequency (<i>FM</i>)	1 lift/min	1 lift/min
Load weight (<i>L</i>)	18 kg	18 kg
Recommended weight (<i>RWL</i>)	8.58 kg	15.75 kg
Lifting Index (<i>LI</i>)	2.10	1.14

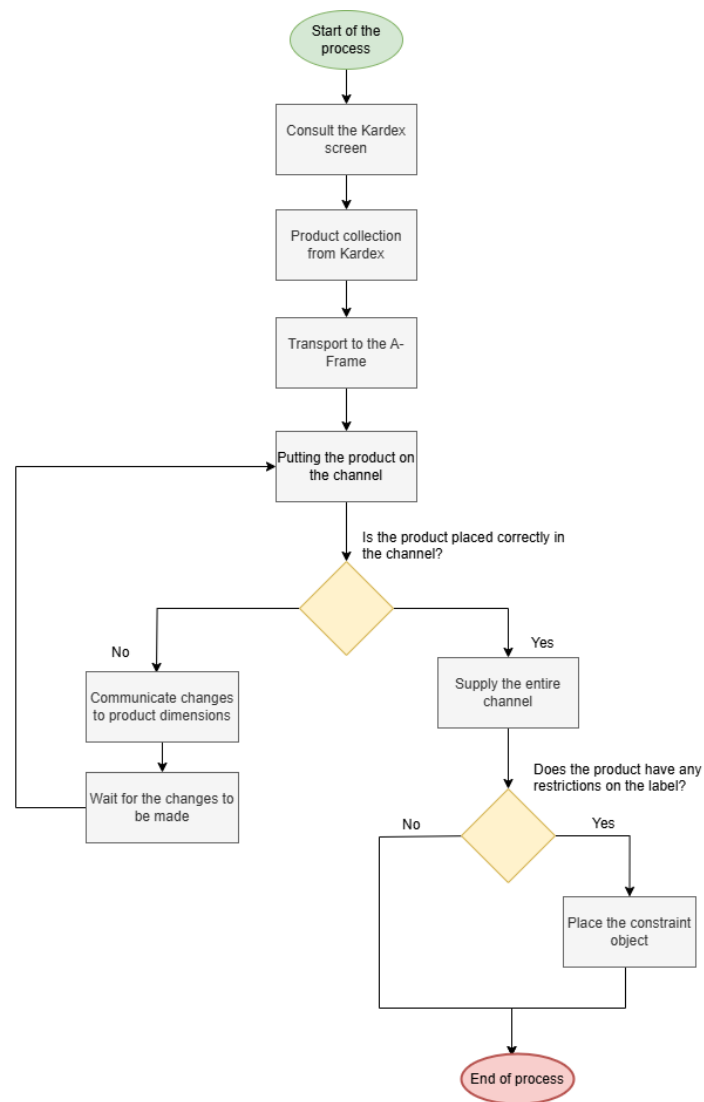


Figure H.4: Detailed process of supplying channels with Kardex

H.2 Details of the Financial Analysis

Table H.2: Estimated Initial Investment per Solution

Solution	Initial Investment	Remarks
Kardex	€603,000	Implementation of 9 modules (3 per side on the 3 sides of the A-Frame), with Power Pick System, installation, and transport included.
Wiimer	€24,500 + VAT	Includes algorithm, Power BI dashboard, and integration with the ERP system. Does not include post-delivery maintenance. Additional cost of €6,400 to €12,800 for visualisation devices as shown in Table 5.1.
Inovesense	€429,800 to 660,000	Includes 138 Cognex cameras, lighting, installation, PDTs, and integration. Average value considered for analysis: €550,000.

Table H.3: Investment summary and breakdown for the Kardex solution

Item	Value (€)
1 × Kardex Megamat 350, 24 shelves	52 420.00
Lighting kit + reference signalling	990.00
Touch console with keypad and emergency button	1 740.00
<i>Power Pick System</i> software with SQL/TXT connectivity	5 350.00
Commercial discount applied	-5 000.00
Transport from Germany	2 500.00
On-site assembly and installation	6 000.00
Total	67 000.00

Table H.4: Estimated Annual Operational and Maintenance Costs
newline (*) Estimated values

Cost Type	Kardex*	Wiimer	Inovesense*
Technical maintenance	€1,500	€4,000	€8,000
Energy consumption	€500	Negligible	€2,000
Licensing and software	€1,000	€0	€2,000
Training and refreshers	€1,000	€2,000	€3,000
Technical support	€500	€1,000	€3,000
Total estimated annual	€4,500	€7,000	€18,000

Appendix I

Strategic Evaluation Framework

Balanced Scorecard: Criteria Definitions and Justifications This appendix provides a comprehensive explanation of the evaluation criteria used in the Balanced Scorecard model, applied to compare the Kardex, Wiimer, and Inovesense solutions. Each criterion is associated with one of five strategic perspectives and has been considered based on its relevance to the operational, financial, and technological context of the company.

Financial Perspective

- **Cost (consultancy, implementation, development and maintenance of AI/ML models):** Total initial investment required to deploy the solution, including integration and external services.
- **Licence cost (if applicable):** Ongoing licensing fees related to software platforms or proprietary tools.
- **ROI (operational efficiency and automation):** Expected return on investment based on productivity, time savings, and process automation.
- **Cost reduction (processes, operation and operators):** Potential to reduce recurring operational costs (e.g., fewer errors, less manual work, optimized resources).

Customers (Internal) – Logistics Department

- **Ergonomics and sustainability:** Degree of improvement in physical workload, posture, and working conditions for operators.
- **Adaptability to current needs (algorithm quality, prediction, accuracy):** Fit between the solution's logic and the actual operational patterns and requirements.
- **Degree of user confidence:** How much trust and comfort users demonstrate when interacting with the system.
- **Customisation for outliers:** Capability to adjust parameters or processes for exceptional products or specific use cases.
- **Interface with AI: intuitive, simple, well integrated?:** Usability and integration of dashboards, alerts, and visualizations with existing workflows.

Internal Processes

- **Implementation time:** Duration required to deploy and stabilize the solution in the real environment.
- **Stock or reserve compaction:** Ability to optimize physical space by reducing unnecessary stock volumes or storage footprint.
- **Integration with ERP – SIDIF:** Technical compatibility and ease of integration with the enterprise resource planning system (SIDIF).
- **Reliability and performance:** System uptime, stability, and overall technical reliability.
- **Replenishment criteria and prioritisation:** Intelligence in the identification and prioritization of items to replenish based on demand or stock levels.
- **Real Time monitoring:** Whether the system enables continuous, live monitoring of stock conditions.
- **IoT connectivity:** Ability to integrate with IoT devices for data acquisition and process automation.
- **Advanced diagnostics:** Level of analytical insights or anomaly detection provided by the solution.

Learning and Growth

- **Innovation – modern, sustainable and scalable solutions:** Degree of technological maturity, modularity, and potential for future growth.
- **Availability of support and continuous evolution:** Quality of vendor support, updates, and improvement roadmap.
- **Training and knowledge transfer:** Ease and effectiveness of onboarding, documentation, and learning processes.
- **Ease of adaptation to future AI projects:** Flexibility and openness of the solution to incorporate future AI use cases or modules.
- **Employee motivation (satisfaction and suggestions):** Positive perception of the solution by staff and their engagement with the transformation.
- **Alignment with company strategy:** Degree to which the solution supports long-term strategic goals and innovation roadmap.

Ethics, Responsibility and Risk

- **Operational risk management with AI:** Controls and safeguards against system errors or unintended consequences of automation.
- **Accountability for automated decisions:** Clarity on responsibility for decisions generated or supported by the system.
- **Compliant and ethical use of sensitive and confidential data:** Ensures that the solution complies with privacy, confidentiality, and data protection standards (e.g., GDPR).

All criteria were scored on a scale from 1 (very poor) to 5 (excellent) and weighted based on strategic relevance. The detailed scores and weighting are presented in the Balanced Scorecard table used for decision support.

Perspective	Criteria	Weighting	Supplier					
			Kardex		Winner		Innosense	
Finance	Cost (consultancy, implementation, development and maintenance of AI/ML models)	8%	3	0.24	5	0.4	1	0.08
	Licence cost (if applicable)	4%	2	0.08	5	0.2	3	0.12
	ROI (operational efficiency and automation)	4%	4	0.16	5	0.2	3	0.12
	Cost reduction (processes, operation and operators)	6%	4	0.24	3	0.08	3	0.18
	Ergonomics and sustainability	4%	5	0.2	2	0.08	2	0.08
Customers (Internal) – Logistics Department	Adaptability to current needs (algorithm quality, prediction, accuracy)	4%	4	0.16	5	0.2	4	0.16
	Degree of user confidence	2%	4	0.08	4	0.08	3	0.06
	Customisation for outliers	2%	4	0.08	5	0.1	4	0.08
	Interface with AI: intuitive, simple, well integrated?	2%	3	0.06	5	0.1	2	0.04
	Implementation time	6%	3	0.18	3	0.18	3	0.18
Internal Processes	Stock or reserve compaction	8%	5	0.4	2	0.16	2	0.16
	Integration with ERP – SIOF	8%	5	0.4	4	0.32	3	0.24
	Reliability and performance	6%	5	0.3	4	0.24	5	0.3
	Replenishment criteria and prioritisation	6%	5	0.3	5	0.3	5	0.3
	Real Time monitoring	2%	5	0.1	2	0.04	5	0.1
	IoT connectivity	2%	4	0.08	3	0.06	5	0.1
	Advanced diagnostics	2%	4	0.08	5	0.1	4	0.08
	Innovation – modern, sustainable and scalable solutions	2%	4	0.08	5	0.1	4	0.08
	Availability of support and continuous evolution	4%	5	0.2	4	0.16	4	0.16
	Training and knowledge transfer	4%	5	0.2	4	0.16	3	0.12
Learning and Growth	Ease of adaptation to future AI projects	2%	3	0.06	5	0.1	3	0.06
	Employee motivation (satisfaction and suggestions)	2%	5	0.1	3	0.06	4	0.08
	Alignment with company strategy	2%	5	0.1	5	0.1	3	0.06
	Operational risk management with AI	2%	3	0.06	5	0.1	3	0.06
Ethics, Responsibility and Risk	Accountability for automated decisions	2%	3	0.06	4	0.08	4	0.08
	Compliant and ethical use of sensitive and confidential data	4%	3	0.12	2	0.08	5	0.2
Total			100%	4.12	3.88	3.28		

Figure I.1: Balanced Scorecard of the solutions under study