Improving visibility of inventory risk at Company X

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Contents

1 Methodology 7

1.1 Company description 7

1.2 Motivation research 7

1.3 Problem statement 8

1.4 Research goal 8

1.5 Research question 9

1.6 Scope of research 9

1.7 Problem approach 10

1.7.1 What information does Company X have about their on-hand inventory that is at risk of expiring? 11

1.7.2 What literature is available to aid in building the tool? 11

1.7.3 Which performance measures should be used in the identification of bad-performing products? 11

1.7.4 Which KPIs should be implemented in the performance dashboard? 11

1.7.5 How to perform a conclusive analysis on product performance? 11

2 System performance 12

2.1 Norm 13

2.2 Reality 14

2.3 Limitations 15

2.4 Shortcomings 15

2.5 Chapter conclusions 16

3 Literature review 17

3.1 Classification techniques 17

3.2 Measurements of expiring products 18

3.3 Chapter conclusions 19

4 Tool design 21

4.1 Performance KPIs 21

4.1.1 Weekly value at risk 21

4.1.2 Days forward coverage 22

4.1.3 Blocked stock 23

4.1.4 Previously disposed stock 23

4.1.5 Fill rate 24

4.1.6 Inventory turnover ratio 24

4.2 Driver KPIs 24

4.2.1 Excess inventory 24

4.2.2 No forecast production 25
4.2.3 Production vs Actual Sales 25
4.2.4 Actual Production vs Planned Production 26
4.3 AHP selection process 27
4.4 Chapter conclusions 29
5 Analysis and Results 30
5.1 Performance KPIs results 30
5.1.1 Value at Risk 30
5.1.2 Blocked Stock 31
5.1.3 Days Forward Coverage (DFC) 32
5.1.4 Previously disposed stock 33
5.2 Driver KPIs results 34
5.2.1 Excess inventory 34
5.2.2 No forecast production 35
5.2.3 Plan to production (PTP) 36
5.2.4 Sales vs production 36
5.2.5 Analysis of the final results and Root Cause 38
5.2.6 Tool testing 39
5.3 Chapter conclusions 40
6 Conclusions and recommendations 41
6.1 Conclusions 41
6.2 Future recommendations 41
7 References 43
8 Appendix 45
8.1 Graphical representations 45
8.1.1 Excess production description 45
8.1.2 Production planned, production actuals and sales performance 46
8.1.3 Value at risk and Previously disposed inventory 47
8.1.4 Blocked stock and Days forward coverage 48
8.1.5 Values that had to be disposed of between 2023 and 2022 49

Terms and abbreviations

AHP= Analytical Hierarchy Process

BBE= Best Before Expiry

BU= Business Unit

CFR= Case Fill rate

COGS= Cost of Goods Sold

DFC= Days Forward Coverage

GAS= Germany-Austria-Switzerland

KPI= Key Performance Indicators

MAPE= Mean Absolute Percentage Error

N3M= Next three months

NOD= Note of discontinuation

PTP= Plan to production

RQ= Research Question

SCL= Supply Chain Losses

SKU= Stock Keeping Unit

SOG= Stock on Ground

SS= Safety Stock

T-BBE= Trade- Best Before Expiry => date before products need to be sold

UKI= United Kingdom-Ireland

USD= US Dollar

Management Summary

The research behind this paper was conducted at a company which is part of the fast-moving goods industry, producing perishable products for multiple retailers around the globe. Given that it has an important portfolio of products, as well as a strong brand, the business produces large quantities of inventory. The core problem that arises from this is that part of the stock produced for their customers never ends up leaving the warehouses and needs to be disposed of in the end. This leads to considerable financial losses, but also social and environmental ones, that affect the company's identity in the long term. Thus, the core problem is how to reduce inventory that is in danger of expiring and what future measures can be taken to ensure consistency regarding this issue. The research process and design were done based on available data from the supply planning team of the company.

Performing a literature review revealed that a suitable way of keeping track of performance is defining measurements to quantify the gap between the norm (the ideal state where almost no losses are caused by the expiring inventory) and reality (the current scenario where too much must be disposed of). Previous works on inventory measurement revealed that setting up a pool of Key Performance Measures (KPIs) can help quantify the gaps and improve inventory performance. Moreover, various authors pointed out that having numerous indicators in the desired tool increases complexity while decreasing the potential visibility towards the stakeholders. Thus, the choice was made to categorize a selection of appropriate limited KPIs. The method used is the Analytical Hierarchy Process (AHP). Each KPI was presented, together with their explanation, thresholds, and formulation (whenever it was the case). The AHP was then applied based on the input of a few chosen employees from the supply planning team of the company. The final list of KPIs includes "Value of inventory at risk", "Blocked stock", "Days forward coverage" and "Previously disposed stock value".

The tool proposed by the researcher towards the business actors consists of a PowerBI dashboard showing a fusion of KPIs (according to AHP). The tool includes multiple graphical representations meant to give the potential user a better understanding and visibility of the current situation of the risk inventory. Furthermore, historical data is used to aid the user in analyzing potential root causes of the current scenario, as well as aggregate on multiple graphical representations, based on their requirements.

The final chapter of the paper presents the most relevant results based on the created tool. Each KPI has a subsection with its most important findings and results. The aim is to find potential patterns that may reveal a deeper cause that can be actioned by the decision-makers. All the findings are put together in a short subsection for a root cause, presenting the main points that could be drawn after the analysis of the results.

The conclusion that could be drawn based on the work done is that forecast accuracy is the main driver that leads to increases in the stock that needs to be disposed of. From 2022 to 2023 there was a 72% increase in the total expiration risk of the business (measured in cases that had to be disposed of), and the quantity that had to be disposed was almost double in 2023. The forecast accuracy was assessed using the Mean Absolute Percentage Error (MAPE) methodology, where the company scored 26%. The aggregation level was made at a factory level, over a 52 weeks period. Based on industry practices, this score translates into a somewhat reliable forecast, but not accurate enough to prevent future losses. One reason which can explain the significant difference between forecast and actual sales could have been caused by a bias in the forecast. The bias could have been part of the forecast that was finalized by the demand planning department. However, based on calculations performed, it was revealed there is no exact bias in the forecast, as the forecast difference against sales can vary between 2% and 61%. This conclusion also eliminates the possibility that the production did not follow

the set plan by the demand team. The main future action that can recommended to the decision-makers of the company is to assess the current forecasting errors and strive to improve the forecast accuracy. The potential improvement that Company X can see if significant improvements are made in the MAPE score is around 20% of the total cases that had to be disposed of. For that, a reduction from 26% to 20% in MAPE needs to be achieved by the business. Moreover, the supply planning team must quarterly assess the target levels set for their Stock Keeping Units (SKUs) and product categories, to improve the performance of the sale.

1 Methodology

1.1 Company description

This thesis will be conducted based on a problem that was perceived by the management planning team at Company X. The company represents one of, if not the biggest enterprises in the food market, with a vast product portfolio. Because they are active in multiple parts of the world, this portfolio is also dependent on the market they are selling.

In terms of culture, the business is "obsessed'' with its customers, as they represent their source of revenue. They strive to keep a high level of customer satisfaction throughout the continents, while also having a high shelf occupation rate. As such, this translates to a significant production rate to accommodate these requirements, which leads to overproducing and crowding of their warehouses. The problem that surfaces from this will be discussed in the subsequent sections.

1.2 Motivation research

As the goods that the company produces are part of the food market, they are regulated to have a date of expiration, before which the customer is advised to consume them (Best Before Expiry or BBE). However, as the business does not directly provide its products to end consumers, it uses intermediaries, also known as retailers in the supply chain. These retailers have also their own set of requirements to conduct their businesses, one of which is to have an extra amount of time available before the goods expire. This can be easily explained if it is considered that the goods require a long enough available time for the customer to even consider them, but also, they spend extra time on shelves before they are purchased. Moreover, retailers themselves keep extra inventory in their deposits to replenish the shelves. Hence, the result is that the business should deliver their products to the retailers with an appropriate minimum remaining shelf life. This remaining shelf life is agreed upon beforehand with the retailers and depends on how they conduct their business (more on the premium pricing strategy, available space in their warehouses etc.). This also depends on the country in which it is sold and the type/category of the product (sauces, infant food, canned food). For that, the company defined another deadline for selling their products, called Trade-BBE (T-BBE).

Referring to the above, the business tends to overproduce and crowd its warehouses. This translates into finished products staying and even expiring into the company's deposits, leading to unwanted supply chain losses. This issue was defined as "Low health inventory level", where the health level indicates the amount of time that a certain Stock Keeping Unit (SKU) has until it cannot be sold to a retailer. The company at which the assignment took place divided these SKUs into "risk buckets", to better represent the level at which a certain one is at.

These risk buckets are also relevant for managing sales. Depending on the amount of time left until T-BBE, the goods in those categories are assigned a priority of selling as soon as possible. Worth mentioning is that multiple batches of the same type of product can have different T-BBE, depending on when it was produced. For example, a product that would have two weeks left until T-BBE would be assigned as priority number one to be sold to retailers. Of course, there will be an extra discount that will be made for those SKUs, depending on the amount of shelf life left that is available. There are cases in which the discount is so big, that the added profit would be almost null, however, this is still more desirable than destroying the products (also known as SKUs Past T-BBE). This is because the business also pays extra to dispose the expiring products, which further leads to perceived losses and would also translate into food waste that harms their environmental identity.

1.3 Problem statement

Following the two previous sections, the action problem that this thesis focuses on is defined, namely: "**At Company X, the inventory has a low health level, meaning that the period in which the products can be sold to the retailers, is smaller than intended, leading to financial losses**". By itself, the action problem cannot be solved, as it is too broad and lacks a clear direction. The problem of bad-performing products can be solved in numerous ways, depending on the scope and design decisions that are made. These two topics will be later illustrated. However, this lack of direction means that, for the research to be developed and a solution found, the investigation process should be directed towards another problem, that is derived from our main issue (action problem), and that contains only an independent variable, which can be manipulated and measured by the researcher.

The issue that is being selected to be influenced is called a core problem. In this case, the one selected is: "**Currently, Company X does not have a clear picture of their bad-performing products that cause supply chain losses**". This was selected because of the interviews conducted with the management team that perceives the action problem. While the problem of bad-performing inventory can be caused by issues in the planning, production, or forecasting (sales) departments due to inconsistencies, it was agreed throughout the interviews that there is no clear image yet in which section or department this problem occurs and the data that is provided towards the business units (BUs) is unclear and lacks ownership (someone who is held accountable over it). Because of a lack of visualization, no prompt action can be taken, so, the first step that is required is to create this general view, from which other interventions can be designed later. The problem of unreliable data is also an important issue that the company faces, however, it was decided that it cannot be influenced using research methods, as it is rather more about policies and rules that need to be implemented for the employees internally. Hence, in the decision-making process, it was chosen the before-mentioned core problem as the issue that will be tackled in this assignment as it is predicted that it will solve the main concern.

1.4 Research goal

The focus of this assignment (and research) is to help the executives in their quest to solve the action problem, namely the low inventory health. The scope of the research will be further detailed in Section 6 of this chapter. It is relevant to mention that the proposed solution is the one that must enhance and improve the visibility problem experienced at the company. As mentioned in Section 3, in the research process, visibility was uncovered as the core problem that can influence and solve the inventory levels issue.

The goal that is proposed for this research project is to develop a tool to ensure that future problems related to inventory performance do not occur as often and can be easily identified. Hence the potential supply chain losses caused by a lower level of inventory health would be reduced. The tool to be developed for the management of the company is a dashboard that should contain the most relevant KPIs and requirements, in accordance with the management team. Hence, the design of the dashboard should be easy to understand and use and should bring visibility towards the inventory. The main data sets that will serve as input for the dashboard will be based on the inventory files that are already available at the company.

Besides the mentioned tool, an analysis will be conducted based on the results and observations from the dashboard. This analysis is meant to accompany the tool and to provide a detailed description of the main problems that are uncovered: the SKUs which do not perform as intended, the countries and factories where the troubles occur and if any patterns can be observed. Of course, due to time constraints (that will also be discussed in Section 6), only a selection of "main offenders" will be made, as those SKUs can serve as an example of interventions that can be designed later for other products.

All of those before mentioned will conclude into a summary report meant for the management team and the main Business Units (BUs) and should also serve as a future reference for potential further actions.

1.5 Research question

To solve the already mentioned core problem, it is necessary to define a set of questions that will guide the assignment throughout the whole process. This set will contain one main research question which, by solving it, the core problem should be also solved. Based on previous studies in methodology conducted (Heerkens & Van Winden, 2017), research questions also need supportive sub-research questions, to divide the main, complex one, into smaller, more manageable parts that are easier to solve and flow naturally from the initial ones (Heerkens & Van Winden, 2017). Thus, the following questions have been defined:

RQ- "How can Company X make use of data visualization methods to improve their low health inventory in the Western Europe market?"

SRQ 1- What information does Company X have about their on-hand inventory that is at risk of expiring?

SRQ 2- What literature is available to aid in building a tool to help visualizing their low health inventory?

SRQ 3- Which performance measures should be used in the identification of bad-performing products?

SRQ 4- Which KPIs should be implemented in the performance dashboard?

SRQ 5- How to perform a conclusive analysis on product performance?

As an overview of the expected deliverables of the (sub)research question, the first two are meant to get more knowledge related to the core problem, through data-gathering methods, such as literature review or interviews, and to have a better understanding of what needs to be included inside the tool that will be later developed. The next two questions (SRQ 3 and SRQ 4) follow from the previous two and are defined to help build the tool and create the research design behind it. At those stages, the dashboard will be built, and certain knowledge is required for that. The final (sub)research question is meant to analyze the results obtained from the tool and create a summary report based on that (Section 4 for reference). A deeper dive into the deliverables from each of the research questions can be found in Section 7.

1.6 Scope of research

Because the problem that is intended to be solved can refer to many SKUs and regions in which Company X sell their goods, the deliverables, and the research behind it should limit themselves and have certain boundaries. Due to the time constraint in which the project will take place, certain limitations need to be set that will be addressed throughout the process.

Firstly, because the assignment is given in the Netherlands, the available data is only based on the European market and is not extended to any other continents. Moreover, as the enterprise is divided between many BUs to work easier on day-to-day activities, the tools will also be developed based on the data from one of the BUs, mainly the Western one. This unit's work is based on the Western part of Europe and will focus on the inventory that is being produced for the UK region and the Continental Western part of Europe (France, Italy, Germany, Benelux etc.). Data that will be used is for a total of eight countries, which will be used for further analysis and visual representation, based on a mix of benchmarks, such as the amount of risk (in cases and currency), risk contribution versus sales contribution (revenues) etc. In the same way, the number of factories is "high", and cannot be easily estimated, however, an initial distinction will be made. The business utilizes internal (primary) and external (secondary) manufacturing sites for the productions (meaning that part of production is also outsourced), depending on forecasts and seasonality. This also implies that the total number of active factories at a certain point in time varies and a total estimate of the number cannot be estimated correctly, so it will be referred to as only being "high". As revealed from the interviews, the internal factories represent a high priority to analyze, as they are the ones that produce the highest volume and are constantly active, whereas the external sites represent more of an aid when the production requires further assistance. Also, it is worth mentioning that the data for internal factories is cleaner, consistent, and easier to manipulate when performing a selection analysis; external sites revealed more inconsistent results in the analysis of the sources available.

Secondly, it is recognized that the amount of goods that leave the factories is considerable, and this is also reflected in the data sets that will be used. Because of that, the SKUs that will be utilized need to be filtered based on the degree of risk and risk bucket in which they are. Again, due to time constraints, it is important to make this selection, however, the data that will be analyzed has to be comprehensive enough and relevant for the rest of the sets from which is selected. The exact number of SKUs that will be considered is not clear, but they will be added to the tool and analysis based on the priority of requirements needed (Section 2), as they are the main SKUs that bring risk: priority number one that expire soon, priority number 2 that will expire soon enough, but have some time left to be sold etc. Again, due to time constraints, only priority one and two will be utilized as input for further analysis, because they are also the products that have the highest chance to have a pattern of bad performance. For the overall selection process, many techniques can be used to ensure that a clear and accurate choice is being made, for example, a Pareto analysis (20% of the SKUs produce 80% of the total risk and losses), as well as other that will aid the research process further down the line (Chapter 3).

1.7 Problem approach

The type of research approach that is selected to solve this assignment is going to be a mixture of quantitative and qualitative. The purpose of qualitative research refers to "researcher immersion in the phenomenon to be studied, gathering data which provide a detailed description of events, situations and interaction between people and things"(Carson et al., 2001). "Qualitative research is designed to tell the researcher how (process) and why (meaning) things happen as they do"(Cooper & Pamela S. Schindler, 2013). Meanwhile, quantitative research refers to manipulating, measuring, and testing the data that is being worked with. While qualitative research tries to understand and interpret data collected, quantitative techniques try to describe, explain, and predict (Cooper & Pamela S. Schindler, 2013). Furthermore, the same authors recognize that "qualitative techniques are used at both the data collection and data analysis stages of a research project". Hence, it is recognized that there is no best approach for this assignment, as both types of research will be used throughout the project, thus a mixture of quantitative and qualitative is favoured. This is in line with the current design, as the data-gathering methods that will be used will try to explain why the management problem occurs and what solutions can be generated. Also, the analysis of the results from the dashboard will have a quantitative nature, as the researcher will try to find patterns and solutions for the root causes. Besides that, the summary report that will be later generated based on the results and the dashboard will answer how can the problem be further solved.

Coming back to the data-gathering methods, those are essential to answer the proposed research and sub-research questions above. According to (Heerkens & Van Winden, 2017), each research question is part of a research cycle that has as an end-product expanding knowledge and moving closer to solving the general managerial issue. In practice, there are a multitude of techniques that can be used, however, for this assignment the most relevant ones used and that will be handful will be mentioned. A description of what is needed and how it will be accomplished per research question will follow in the next sub-sections.

1.7.1 What information does Company X have about their on-hand inventory that is at risk of expiring?

For this (sub)research question a preliminary incursion in the files/artifacts and previously produced reports will be made. The goal is to understand what type of information is available for the researcher and to assess the current performance of the system on the proposed action problem (the low health inventory). Activities such as data cleaning and data collection will be performed to arrive at a conclusive answer.

1.7.2 What literature is available to aid in building the tool?

For this sub-research question, literature review will be required to answer it. The aim will be to build enough background knowledge to understand what type of tool it should be and what it should contain. Furthermore, aggregation and selection techniques will be searched for to aid in building the tool according to a set of requirements. Because of the significant sizes of the records available, it is acknowledged that not all data and not all potential measures can be part of the final tool, proving the need for a literature review at this stage.

1.7.3 Which performance measures should be used in the identification of bad-performing products?

A literature review will be conducted to answer this one. Structured or semi-structured interviews can also be conducted to gain more insights into the performance measures that are being used inside the company. These interviews may require the approval of the Ethics Committee, as the data collected is sensitive and needs to be handled carefully.

1.7.4 Which KPIs should be implemented in the performance dashboard?

For this sub-research question, it is intended to collect data through interviews with relevant employees from Company X, such as production planners, or specialists in supply chain losses inside the company. The importance of their opinion and input is critical, as the tool is intended to aid their daily work in preventing expiring products from being destroyed. A secondary data analysis will also be performed to check for previous decisions and interpretations of data that were documented inside the company. Secondary data analysis is simply reviewing artefacts and documents previously produced inside the company for personal use(Cooper & Pamela S. Schindler, 2013). All these techniques mentioned should help in implementing the dashboard for the company, as this is the phase where the design of the tool is being developed through research.

1.7.5 How to perform a conclusive analysis on product performance?

As for the other sub-research questions, a mix of literature review and interviews will be conducted. A root cause analysis should at least be provided inside the report, to give a better perspective towards the decision-makers of what can be changed/optimized. The literature review will be used again to expand the knowledge and have a better overview of the possible solutions. This phase of the research is critical, as this is where the results obtained from the tool will be addressed and new suggestions and interventions can be designed.

2 System performance

In this chapter, the focus will be put on answering the first research question, namely: "*What information does Company X have about their on-hand inventory that is at risk of expiring?*". Solving this question is of great importance, as its goal is to assess the current situation of the system and understand what an ideal state should be. This process was described by (Heerkens & Van Winden, 2017) as understanding the gap between the norm (what is the desired situation) and reality (current situation). For that, the available data that is provided by the company needs to go through cleaning and selection, as not all information that is in their databases would be useful.

The main activity that needs to be worked out in this stage of the project is to define a way of measuring the mentioned gap. The chosen solution is to quantify the current issue, by assigning a proper value to it to reflect the progress in solving the problem. By considering the core problem that inventory is expiring inside warehouses, it is determined that the gap between norm and reality should be measured in the potential losses that are observed. In this case, losses are simply products that need to be disposed of, as their trade before-expiration value is past an acceptable one and the product cannot be sold anymore. It can be perceived either in terms of cases that are being disposed of or in terms of USD that are being lost. Both are relevant to consider when assessing losses, as there are scenarios in which a bigger inventory does not automatically mean a high $ value. Even so, it is also worth considering the amounts in cases (or pallets) because those contribute to overcrowding the warehouses, which leads to potential extra costs as well.

Referring to Chapter 1, Company X already divides their inventory into buckets of risk, depending on how much time available they have (time before the expiration date). This division represents an industry standard, which is common for companies with perishable inventory. Hence, the business uses in practice five categories, mainly: 0-30, 31-60, 61-90, 91-120 and >120 buckets in days for their inventory at risk of expiring. An extra two buckets which contain products that cannot be sold are also used, "Past T-BBE" and "Past BBE". The latter two are in place to reflect the items which will be disposed of and that would not be accepted by any retailer in any case, such that those can be considered actual losses that the company will have, and not potential risk as for the other five mentioned. Once it is produced, a batch of a product automatically enters the lowest risk bucket and flows normally from one bucket to another, depending on the available time left before T-BBE, thus having enough time to stay in warehouses.

However, this division does not reflect fully the potential losses that may occur. A product that is in the highest risk bucket (0-30 days available before expiring) can still be sold through sales promotion to certain retailers, hence it has a salvage value that the business can still obtain. The same can also be applied to other buckets of risk. Even though the value can be so small that they end up breaking even for that batch of the product, it is still more desirable than having a loss because they cannot be sold anymore, as well as paying extra to dispose the batches. The assignment will not focus on the products which are sold for a discount, but rather on those that will become obsolete and need to be destroyed, as those are considered the main problem as of right now. After an analysis of the data, it was revealed that the value of the products that will be disposed increases over time (Figure 1, when assessing the graph for 0-30 bucket) which means that over the years more value is lost. While this can be attributed to higher production rates from factories, it still can be viewed as unnecessary losses that the business encounters and the value at risk in the 0-30 bucket (highest risk level) will in most instances translate into products that need to be disposed of. Worth mentioning is that the company has a policy of make-to-stock for their inventory, which means that they produce depending on the levels of their warehouses. Once the level falls below a minimum, the system plans another batch to be produced, depending also on a mix between the amount that was lastly subtracted and produced the shortage and the incoming demands for that certain product. This only emphasizes the need to solve the problem of products that enter the highest level of risk currently, as those SKUs are more likely to translate into a loss. The logical step that was taken after that was to formulate a measurement method to aid the research, which will formally be the potential USD and cases that are at risk in buckets. The focus of the research will be put on the immediate risk (0-30) one hand to identify and possibly alert planners of potential imminent risk, but also due to the time constraints mentioned in Chapter 1.

2.1 Norm

The ideal situation (the norm) should reflect what is the state that the current system should attain to. In theory, this should be the goal for the solution that will be generated. However, as revealed from interviews with the management planning team, there is no current state which can be considered a desirable level for the inventory health problem. Hence, one of the steps that needs to be taken is to study historical data inside the company to analyze the trends from previous years. Information regarding the numbers for products at risk as well as products expiring will be collected for further analysis. The scope is to get a clear picture of the historical inventory evolution and to present how the losses increased and by how much. Those trends can then be used for comparison with the current performance of the inventory. Because the data that is available from the business starts only from 2020, the analysis will be conducted on years from 2020 to 2022.

Furthermore, the average value at risk throughout 2020 to 2022 is shown in Figure 1, with the mentioning that the year 2020 has data available only starting from week 25. The value presented on the left side of the view is also dependent on the risk bucket. This way, the comparison can be made adequate to check for anomalies and how the values at risk evolved from one year to another. While it can be considered sufficient to show that there is a problem inside the system from comparison, a threshold goal can also be established based on the norm. Although it is not an ideal number, as the available data is limited, it might still be worth determining for future explorations. The value selected for threshold per year per bucket can be found on the left top corner of Figure 1 and represents the average value at risk in a year, in a specified risk bucket and the graph associated shows inventory risk evolution throughout the weeks of the year. As an example, the view presented shows a threshold for the quantity and US $ at risk 0-30 days. The norm value in Figure 1 in this case will be around $1.2M and 411K cases. Multiple thresholds can be determined, depending on the risk buckets we explore for.

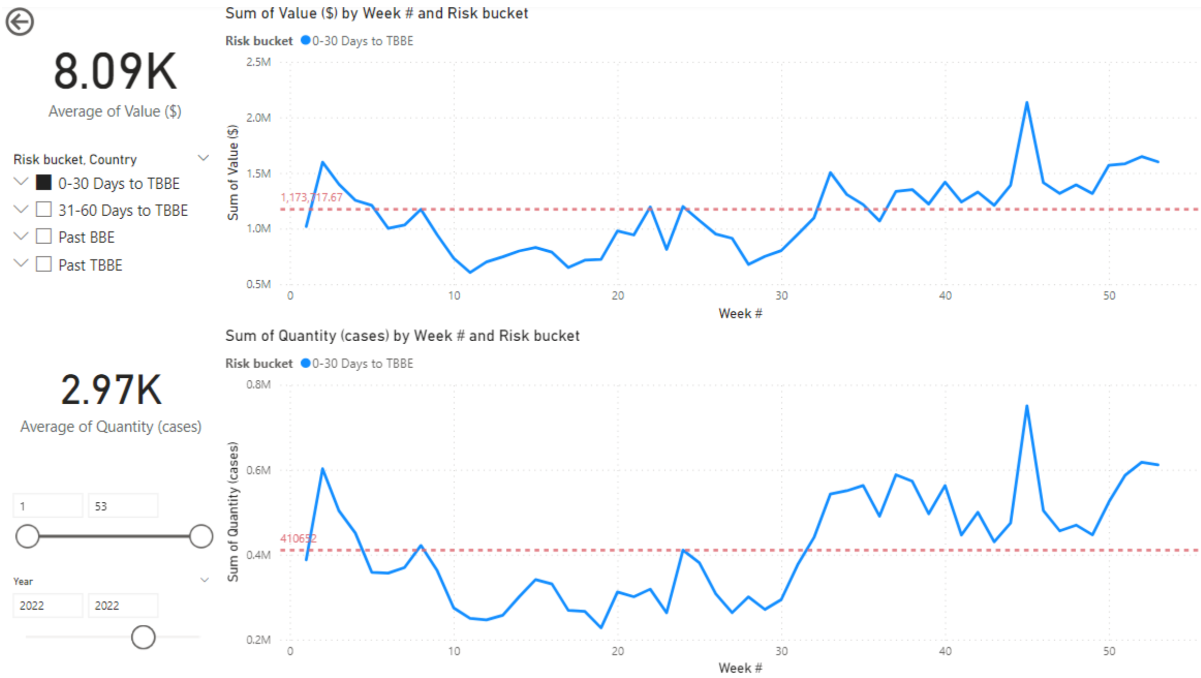

Figure 1: Risk evolution in bucket 0-30 during 2022, in dollar and cases

2.2 Reality

The current situation is a snapshot of how the system currently performs. In the case of Company X, that is how much value that they have in inventory on hand is at risk of expiring, producing further losses. One way of evaluating that is by checking the available data between the first fiscal week of 2023 and another arbitrary fiscal week of this year (2023) to see how the situation developed in that snapshot and how much value at risk was acknowledged inside data files. As can be observed by studying Figure 2, the amounts on average based on the 0-30 days bucket (left side of Figure 2) are larger than the threshold example ($1.2M) that was established in the section above. This confirms the assumption that currently, Company X has more value at risk than in previous years, which will also result in further losses. The snapshot presented is from week 1 to week 12 of the current year and the values noted are the averages throughout those weeks. Further observations can be made based on the available data on products that already expired and caused losses. The values for the year 2022 (Figure 22 in Appendix 8.1.5) are lower than those of 2023 (Figure 23 in Appendix 8.1.5), for the same period of the first 12 weeks, which indicates a trend of extra losses that Company X has. The goal will be to analyze in more depth those values by visually representing them and finding the root causes that can explain the sudden increase of inventory in risk buckets.

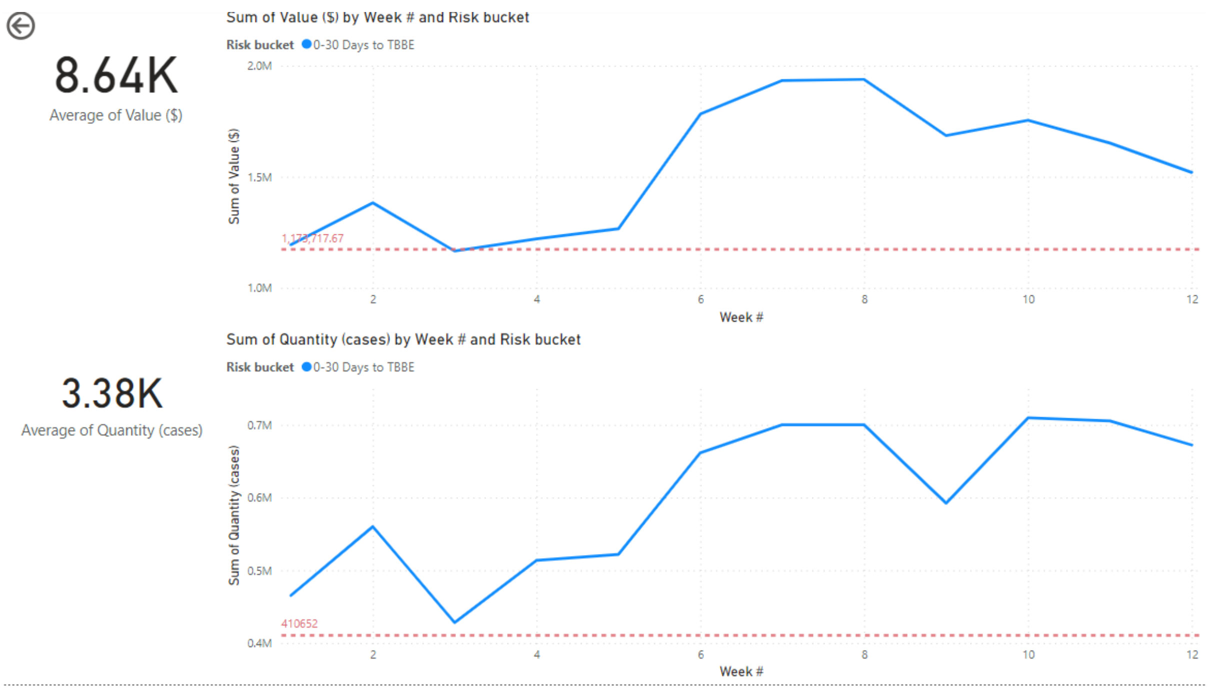

Figure 2: Risk evolution in the 0-30 bucket during the first 12 weeks of 2023, in dollar and cases

2.3 Limitations

In this subsection, the limitations and shortcomings of the system will be discussed. These are relevant for the research process as they will influence the design stage of the project as well as the data that will be used when building the tool and analyzing the results at a later stage. Firstly, it is relevant to mention that while the datasets made available by the company are comprehensive and contain enough information to work with, they are also limited in terms of historical data. This is because while the employees keep track of their inventory progress on a weekly and monthly basis, it becomes tough to store historical data from multiple previous years. The implication is that the analysis that can be conducted on what is available may not present 100% accurate results, but one that improves on the previous states of the available years. As mentioned in the general limitations and scopes of the project in Chapter 1, the available time to perform each stage of the project is also constrained to ten weeks in total.

2.4 Shortcomings

In terms of shortcomings perceived, the company uses multiple integrated systems for their planning demand activities. While in theory, these systems should use the same data and output the same results, in practice, this is not completely true. In multiple instances, it was observed that there was a discrepancy between available data in terms of numbers and information regarding production. This issue may reflect on both the integration of the tool and the analysis of the results in later stages. To tackle this shortcoming, there are two possibilities: either the same system and sets are used throughout the project and base all integration on that, despite potential numerical abnormalities, or check the source which provides the data closest to reality. While the latter is not fault-proof, it can be achieved by double-checking with the employees and studying previous data for consistency.

Another potential issue that can arise is in the design phase which refers to the SKU codes that are used inside the company. It occurs that in some instances, products had their codes changed from one year to another, despite having the same production formula. For those products, historical data is more difficult to track and provide a concise picture. One workaround that can be used is to use the product categories and product descriptions inside the views and analysis or link multiple SKU codes with the same product (whenever it is feasible). The drawbacks are on one hand that the amount of information will be complex to implement, due to extra data that needs to be included, but also that there needs to be a clear set of associations that contains all previous combinations of codes and product names.

In addition to that, the available data regarding production in factories of SKUs does not contain any information about the country in which it is produced. The only geographical indication that is presented is about the site where it is produced. This is because the records do not keep track of the amounts produced for each country, but instead the level of the inventory for particular products. This may interfere when comparing the volume sold versus those produced for different countries. In that case, the only option at hand is to compare based on the products themselves, and not analyze fully based on only regions.

2.5 Chapter conclusions

The data sets that are made available provide a clear enough picture of the current situation regarding the issue of inventory health inside warehouses. With large bases provided, the norm (a goal that should be attained) will be the historical evolution of the potential losses based on buckets. Furthermore, for better measurements, a certain level can be established by considering the average potential losses in terms of cases and USD of the same historical data. The available data shows, at the very least, SKUs that are in different risk buckets, amounts on hand that need to be sold and their value, as well as products that expired together with their lost value. Information found is sufficient to answer the (sub)research question: "*What information does Company X have about their on-hand inventory that is at risk of expiring?*". Furthermore, there is available information inside the documents that can further broaden the picture and aid the inquiry made. Main takes of this chapter:

- The measurement method that will be used will be the potential value at risk (USD and cases)
- Current values of the stock present a higher risk in 2023 than the trends from 2020-2022.
- Historical records on risk buckets provide the starting point for future designs that can be proposed to the decision-makers
- A root cause analysis can be further developed in later chapters based on what is available.

3 Literature review

This section is meant to give an overview of the literature that will be used throughout the project. While this data-gathering method can be used during multiple stages of the research as a means of expanding the necessary knowledge, it will be used in this instance to solve the second proposed (sub)research question *"What literature is available to aid in building a tool to help visualizing their low health inventory?"* and the third one *"Which performance measures should be used in the identification of bad-performing products?"*. The main goal will be to discover relevant works about obsolete inventory and other measures that relate to it, and how to classify them.

As it was established in Chapter 2 there is a gap in the system behavior between what is expected and what is observed, the step that follows from there is to uncover a way of determining and differentiating between multiple SKUs that have a performance issue. In this instance, the research process is not interested in quantifying the gap (as was the case in Chapter 2), but in finding relevant measures to divide the bad-performing products from those that are stable. Those measures will have different degrees of importance for the management team, as they have certain priorities (such as dollars at risk, sales forecasted correctly, fill rate etc.) when assessing the performance. This classification should also be reflected in the proposed tool. Hence, this first inquiry in available literature will be to determine a way of classifying the inventory measures. During the first "dive", it was determined that a hierarchical classification would be best suited, so the literature at this level will be related to either ABC classification, Analytical Hierarchy Process (AHP) or Multicriteria inventory Classification (MCIC).

3.1 Classification techniques

The literature available on the topic of ABC classification is numerous and proposes to classify the inventory produced by considering the annual dollar usage (G.W. Zimmerman, 1975). This is a common practice in industries that utilize inventory obsolescence and is commonly known also as the 80-20 rule or Pareto rule. The 80-20 rule means that 20% of inventory generates 80% of revenues, or, in the case of Company X, 80% of the value lost. This can be applied to our situation as well, as the Pareto rule is flexible in terms of the representations that can be made. The ABC classification implies that the items assigned to it can be divided into classes, with A representing the most important items and C the least important (Iqbal et al., 2017), each class with its single criterion. This classification system can be viewed as a powerful tool when evaluating the state of the inventory (M.R. Leenders et al., 1985), which confirms the simplistic, yet efficient way of measuring the system gap in Chapter 2. However, as noted by the same authors, in businesses that deal with a high volume of obsolescence, this criterion may not show a comprehensive enough picture and additional criteria would benefit further performance analysis. (Iqbal et al., 2017) argued and demonstrated that multicriteria classification for each of the A, B, and C classes are more beneficial for optimizing inventory decisions than the single-criteria ones, although the latter are more commonly used in industry and are easier to handle in practice. While it is beneficial to consider multiple performance measures within the ABC classification (Flores et al., 1992), it is important to also consider the complexity that this multilevel comparison adds and to try and make it more efficient for both the management and the tool that will track later these measures. One way proposed by (Ramanathan, 2006) is to tackle the complexity issue by considering a range of inventory classification techniques, which can be divided into optimization and non-optimization ones. Due to the limitations before mentioned, only the non-optimization ones will be considered, as they provide a simpler pairwise comparison that is preferred. One technique that is well documented is AHP classification, which is why this model was selected for further investigation.

The Analytical Hierarchy Process (AHP) method was developed to help decision-makers when assessing the criteria that should be considered when performing inventory analysis, as a way of breaking down complex decisions into smaller, more manageable ones (R. W. Saaty, 1987). In its most simplistic form, the technique uses quantitative expression to assess and weigh the importance of each criterion and place them on a hierarchy of relevance for the business case. There are two separate ways of calculating the output, either using specialized programs, such as EXPERT CHOICE (R. W. Saaty, 1987) or in a manual way (Flores et al., 1992), based on straightforward computations and weight assigning. It is worth mentioning beforehand that this method is criticized for its limitations in terms of biases and subjectiveness, as noted by (Iqbal et al., 2017). This will be solved in practice by assessing the weights that will be assigned together with the management planning team of Company X. The validity of the results will be in the end challenged and checked, to have a complete process.

3.2 Measurements of expiring products

The measurements that are integrated later in the tool and analyzed further will be organized as KPIs (Key Performance Indicators). The need for such an organization is given by (Chae, 2009) who emphasizes that KPIs are a useful way of measuring the gap between norm and reality. The criteria that will be considered inside the AHP method should cover the full context of the company's inventory problem and reveal its important statics of it.

As discussed previously in Chapter 2, Company X tries to keep a record of their inventory in terms of the risk to which they are exposed to, dividing all of them into several buckets to better represent that. The KPI "Weekly value at risk" is meant to record and represent that in the dashboards in terms of cases of goods and dollar value at risk, which (G.W. Zimmerman, 1975) also described as useful for his Pareto analysis.

Days forward coverage (or DFC) is a KPI presenting the period for which the current inventory covers the upcoming (expected) demand and was implemented as a means of keeping track of stock fluctuations that may occur in daily activities. According to (Chae, 2009), keeping track of the number of days your goods cover is an industry standard across many domains. Although his formulation is an economical one, the concept of creating a view in days for this measurement will still be useful for the tool.

In their study, (Oliva & Watson, 2007) propose a holistic way of calculating the coverage in days of the inventory. In their formulation, they consider the available inventory at the end of a period, in sales units, divided by the annual order in the same sales units, and multiply everything by 365 days.

The described formula will be used for Closing DFC, but another similar measure can be derived for Target DFC (based on the number of days that the current inventory has as a target to cover at the very least). For this one, the formula is similar, except it is using the Target Inventory instead. As per (Vaz & Mansori, 2017), when safety stocks are being used (which is also the case for a company), the target level in days will be the "safety stock and point between minimum and maximum quantity to order" for a particular SKU. However, because of its holistic nature, this method is prone to errors. The same authors argue that the safety stock level can be chosen based on inventory categorization methods, such as the ABC method, where individual SKUs are divided into multiple categories of importance for the business.

Blocked stock represents the amount of inventory produced by an SKU that is inaccessible due to different circumstances. Relating to our health inventory issues, part of the blocked stock can be because the product has passed the trading date, making it unsellable to any retailer. This inventory state has as a consequence supply chain losses perceived by the company, linking it back to our main research topic. (Ton & Raman, n.d.) proves how a diverse portfolio of products and high inventory levels can cause expensive losses for a business, by introducing the notion of "phantom products". These are products that are already available to the business but cannot be further moved in the supply chain towards the customer. The scenario presented by the authors is similar to the one the company is in, proving that there is a need to define a measure for inventory which is not accessible and will ultimately produce losses.

Product obsolescence is a common measurement that businesses who sell physical products need to keep track of, as it gives valuable information related to the "hidden costs" that they inquire about, such as holding cost, depreciation or disposal cost (Rosenfield, 1989). While most of the available literature focuses on the obsolescence of products with high production costs, high selling value or slow movers, there is not much information regarding products with lower value and smaller product life. However, if we consider that the business packs together its products in pallets, suddenly the values that are deposited in their warehouses increase and becomes less negligible. Another difference in comparison to the classical high obsolescence value products, such as electronics or cars, is that the company's products do not have a salvage value and hence they can only consider the costs associated with disposing the products, and no salvage value. In practice, in many industries enterprises consider the obsolescence value as the difference between the original value minus the salvage value (Vaz & Mansori, 2017), which in this case does not exist.

Another indicator that is considered relevant when studying inventory performance by both (Iqbal et al., 2017) and (Yang et al., 2020) is the order fill rate OFR, which measures the number of orders that can be satisfied based on the inventory on hand, without having stockouts (Yang et al., 2020). It is a market-wide way of understanding whether a company manages to supply the orders that they receive, and to understand in which markets the sales performance suffers due to a poor supply commitment.

Both (Chae, 2009) and (Mentzer et al., n.d.) emphasize the role of sales performance for a company and the value it brings of having the complete picture of it. The production process is based on a plan that is being built by the financial department, which is tasked with "projecting cost and profit levels and capital needs" (Mentzer et al., n.d.), and serves as the driving numbers for the rest of the year. Of course, these forecasts can be adjusted depending on market response and performance over time, but even so, the manufacturing process takes place a year in advance, so the ulterior adjustments in the planning can only impact the production at that moment in time and would not help the inventory that is already available.

(Stevanoski et al., 2022) highlight the importance of measuring the difference between planned production and production that actually took place. Knowing your "production plan adherence %" (Stevanoski et al., 2022) gives visibility if for a certain period, the factory overproduced (excess inventory) or underproduced (gap to plan). This type of view is essential for the business to be fully aware of and have complete visibility of, as they can plan accordingly for the next weeks or months the inventory and capacity needed to be on target (Chae, 2009) and the resources that need to be allocated (Stevanoski et al., 2022).

3.3 Chapter conclusions

To answer the (sub)research questions of this chapter, a classification technique needs to be found to assess the potential measures that will be used when designing the tool in a subsequent chapter (Chapter 4). A weighting system will aid when determining a hierarchy for the SKUs that are not performing well and will help determine which of them should be the focus for later representations and analysis. The future performance indicators that need to be selected need to revolve around the core problem of the researcher, meaning obsolete inventory and what potential causes can be found inside the company, based on the available records. Potential key performance measures are described in this chapter. Future KPIs in subsequent chapters are going to be built based on the literature review and be reviewed for the visualization tool.

4 Tool design

In this section, the design of the proposed tool for Company X will be presented. The tool itself is represented by a Power BI dashboard containing relevant information to solve the management problem that is perceived. This information is presented and calculated as Key Performance Indicators meant to bring clarity for the employees and were discussed with the management planning team, to include the most desired ones. Based on theory (Chae, 2009) , it was also decided to limit the number of KPIs to be used, as a high number would increase the complexity and would not improve the quality of the tool. A literature study was performed to understand the trends and options which can be implemented, based on the data that was made available. (Chae, 2009) helps to better understand the need for such measures for supply chain management. The author highlights that there will always be a "gap between what was planned (by the decision makers) and what was done" and that the "performance metrics offer the visibility" needed to the enterprise. This is because "KPIs reveal the gap between plan and execution and offer opportunities to identify and correct potential problems".

By building this tool, it is desired to answer the proposed (sub)research question *"Which KPIs should be implemented in the performance dashboard?"*, as the selection of the KPIs is included in the design of the dashboard as well.

One important aspect that was stressed out by multiple scientific sources is the need for a clear hierarchy to differentiate between multiple KPIs. The latter's simplistic take on this was to consider the correlation between KPIs, or primary and secondary levels of them. For building the tool, the nature of the correlation will be taken a step further to describe a cause-and-effect relationship, which was also proposed by (Sedrakyan et al., 2019) as a performance-driver relation.

In the current situation of the company for which the research is being built, the visual tool should provide an overview of the primary potential causes of having expiring stock. Hence, the measures which will be shown should revolve around this area and will represent different causes for which the inventory needs to be disposed of. By using primary and secondary data analysis, an immediate set of six KPIs was decided upon to be further represented. The KPIs in question are "Weekly Value at risk", "Days Forward Coverage", "Blocked Stock", "Previous period disposed stock", "Fill rate" and "Inventory turnover ratio". This six KPIs will be included into performance category. This category includes the immediate issues that can be observed within the inventory and which the employees may face on their daily tasks related to core problem. The other category of KPIs which will be used in the tool will be driver KPIs, which represents a possible numerical explanation of the performance issues. These KPIs are related (or maybe even by themselves) to the root causes of the performance ones, and thus, the perceived issues. The driver KPIs selected for the dashboard are "Excess inventory", "No forecast production", "Production versus Actual sales" and "Actual production versus Planned production". A further description of all KPIs will follow in the subsequent sections.

4.1 *Performance KPIs*

4.1.1 Weekly value at risk

Due to time and size constraints, only the immediate and imminent risk represented by batches 0-30 and 31-60 will be implemented for this KPI, as well as the buckets where products are past expiration date (P-BBE) and past trade date (P-TBBE). The value of inventory at risk will be extracted at an SKU level from the company's reports. Ideally, no products should be left to expire in the stock, as it leads to huge losses. Based on the documents provided, the total inventory can be aggregated on multiple levels, such as market or product category, to enable further analysis.

4.1.2 Days forward coverage

The scope of introducing this measurement is twofold. On one hand, if the available coverage is way higher than the target, this means there is an extra stock that may be in danger of getting blocked (see Blocked Stock subsection) or entering higher risk buckets, causing further inventorial problems. On the other hand, if the number is lower than the proposed target, this means that the business may have potentially lost sales and need to overproduce, which can also disrupt the inventorial flow, causing further losses. One potential issue that may occur is that the extra production may also go into the risk buckets. While the lost sales are not an issue concerning the overall inventory health, it is still recognized that it may be helpful to the employees who may use the dashboards.

Drawing a parallel to the formula of (Oliva & Watson, 2007), for the indicator that should be built, similar values can be considered to obtain a holistic formula. The formula by which the DFCs will be calculated is based on the available stock at the end of a period. Two different types of DFCs will be calculated, one for the closing number of days the stock covers, and the targeted number of days the inventory should attain to. Hence, for the Closing DFC, it will be used the stock on the ground (SOG) divided by the next three months' demand (N3M). It represents a holistic estimation of what should be the coverage in days of the stock, which excludes seasonal items. In practice, the number of products of Company X that are seasonal is relatively small, and since the DFCs will refer to the product categories, the aggregation of all SKUs of a product category will minimize the potential impact of a seasonal item. The end-period inventory is used because the needed inventory for the current week/month was already subtracted and is easier to account for what is available, rather than what might be (as it would be when considering the starting stock). The N3M demand is used as a measure of what is expected to be needed in the upcoming period. The choice for three months was aligned with the company to provide a better estimation on a smaller time horizon, rather than the full-year order demand, which was proposed by (Oliva & Watson, 2007). The result of the division is thus multiplied by 91, the average number of days for 3 months:

$$Closing\ DFC = \frac{SOG}{demand\,(in\ N3M)} * 91 \tag{1}$$

The target inventory level can also be set holistically, based on the formula of (Vaz & Mansori, 2017). The limitation of this method is that for a large number of SKUs, throughout multiple portfolios, the task of categorizing them becomes time-consuming and is not the main objective of the research. Hence, instead of recreating holistically the target inventory levels in days for this KPI, the choice was made to use the levels defined by the company for each of their product categories.

Hence, for the formula which will be used, Target Inventory represents the level which is set up by the company for any particular product, such that the amount available should not get below that number. Target DFC is an approximation used by the company to estimate the coverage of inventory in days:

$$Target\ DFC = \frac{Target\ inventory}{demand\,(in\ N3M)} * 91 \tag{2}$$

The choice for having both measures is explained by the fact that management would be interested in both the actual inventory level, but also the above target maximum one when assessing DFC KPI. Hence, a negative value means that the actual inventory is not sufficient, while the above one can translate into overproduction, depending on the managerial decision. Because the target inventory is set considerably higher than the safety stock (**Error! Reference source not found.** 3) and because the business considers everything above target inventory days as inventory risk (Figure 4), the decision was made to follow the same practices, but allow some buffer due to inconsistencies in the data.

Hence, only a 10% deviation of the Closing DFC above the Target DFC will be perceived as an acceptable level. 10% would represent a maximum of 6 days that can be considered as acceptable range above mentioned target, which would imply that the inventory can be held for another week, for certain categories. If the decision was made to allow the Closing DFC up to the Max level, the follow-up actions would have been reactive, rather than preventive, to reduce the potential of excess overstocking.

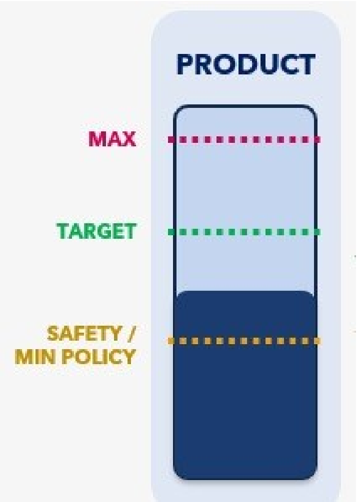

Figure 3: Inventory levels standards

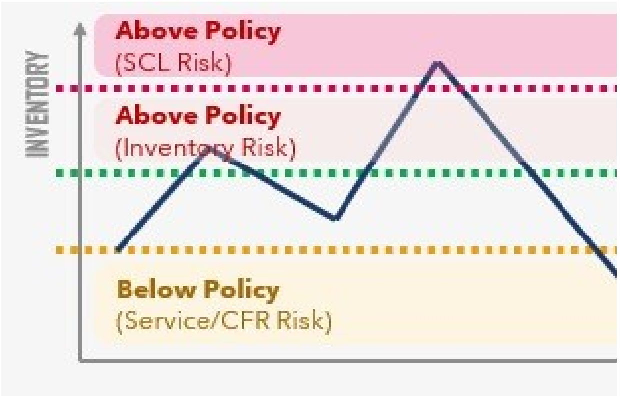

Figure 4: Inventory levels standards

4.1.3 Blocked stock

The blocked state represents the intermediary state between trading and disposing, in which a product did not expire, but will inevitably be destroyed due to expiration if no action is taken. However, the blocked stock does not refer only to the past trade ones, but to other situations, such as blocked by quality issues. For example, if the recipe was not followed correctly in the process, or the packing/labels are not accordingly, the system would block the produced SKU and will not consider it as part of the total stock. The visual KPI does not have a formula to use, but rather keeps track of available information spread throughout multiple sources inside the company, bringing forward the records and making them visible towards the decision-makers.

Because of this distinction between different scenarios for the blocked stock, the available data is also split throughout multiple document sources. One source contains available data of blocked stock based on trading date information, meaning the scenario which refers to expired products, while another source presents the whole amount blocked, indifferent to its provenience. The decision proposed by the researcher was to present both visually. The one based on past expiration dates revealed incomplete data in terms of product categories. This caused errors inside Power BI when connecting with Excel, so the workaround to use the rest of the information was to define the categories for the products with errors as “Not applicable”. As such, the category “Not applicable”, although confusing, allows the management team to sort in the slicers based on other criteria, such as Business Unit or factory, and not limited to incomplete views that would otherwise appear by removing the connection errors.

4.1.4 Previously disposed stock

The business must understand what and how much they lose and have lost historically in terms of having products that expire and keep track of these in a matrix. The performance measure itself is not based on a mathematical formulation, but it keeps track of the recorded amounts and reported back by the company. The previously disposed stock indicator shows what were the amounts that expired and needed to be disposed and caused further losses. This value can simply be associated with the amounts past the expiration date, as essentially, they represent the same thing. As a threshold, it was decided to compare the amount of disposed inventory against 2022 numbers. Because of the disruptions caused by the pandemic, the business had to dispose considerable stock due to expiration. If during the current year, the amount that needs to be cleared is higher than last year, it means the issue needs a closer look. Of course, even being lower is worth looking into, as it provides an opportunity to improve the losses perceived.

4.1.5 Fill rate

Based on the literature review, the fill rate represents a valuable indicator for the supply team of the company as it shows them which orders were not fully fulfilled and if there is inventory produced that was not yet shipped to the retailers. Based on business practices, a good fill rate is somewhere between 90% and 100%, while a bad one should be anything below 85%. The formula for calculating the fill rate, weekly is:

$$Fill\ rate = \frac{orders\ completly\ fulfilled\ during\ a\ week}{total\ number\ of\ orders\ received\ for\ that\ week} * 100 \tag{3}$$

4.1.6 Inventory turnover ratio

Inventory turnover ratio is another KPI related to inventory which is used throughout many businesses which deal with supplying different products. It is a measure that shows how well a company is managing their inventory and if it carries extra inventory in its warehouses. A higher ratio translates in this case to a reduction in holding costs and available inventory. Because the company for which the dashboard is being built is concerned with fresh finished goods that can expire, they must achieve a high turnover ratio and sell their goods, as they can also inquire about the cost of disposing inventory. The formula for inventory turnover on a certain period is:

$$Inventory\ turnovr = \frac{cost\ of\ goods\ sold\ on\ a\ period}{average\ inventroy\ value\ during\ the\ same\ period} \tag{4}$$

4.2 Driver KPIs

4.2.1 Excess inventory

This KPI was designed to keep track of the excess inventory that is produced and is present in the currently available stock. The excess stock build-up can be due to multiple causes, such as slow sales, incorrect production plan reviews or complex demand planning systems not utilized accordingly (Rosenfield, 1989). The excess by itself would not represent a problem for the operations of the company if it were utilized by the Sales department and accounted for by the demand planners when creating future forecasts. However, because of the complexity of the system and human error, the extra that was produced and not sold can be left unchecked in the warehouses, while also being recorded in the total inventory. This can cause batches of multiple SKUs to expire or be blocked inside warehouses, which further produces supply chain losses. Moreover, because the excess represents quantities that were not accounted for in the plans made, they may raise the inventory level on top of the target and maximum allowed level (Figure 4), above which the business would only perceive further risks and losses. Hence, the decision to represent the Excess Production as a KPI was made.

To calculate the excess stock that the company has, a formula needs to be calculated. One simple way of calculating it is by comparing stock at the end of a week after the production took place and shipments were sent against the upcoming demand. As explained before for the DFC performance indicator, demand over the next three months period gives a good time horizon over what is expected to be delivered by the supply planning team towards the markets. Hence, the stock levels for individual SKUs will be refined in the data source to reflect also the cumulative next three months' stock. Because in the planning systems, the demand is dynamic and considers any fluctuation already seen, there is no need to create any deviation from the production plan and overstock. Thus, it is feasible to simply compare the N3M stock against N3M demand:

$$stock(N3M) - demand(N3M) > 0 \qquad (5)$$

If the result of the formula above is greater than 0, it means there is an overstocking scenario, and it will be recorded in the dashboard tool. As there is no reason for actively overstocking and deviating from the plan, any extra stock will be considered excess inventory and above the targeted level (Figure 4). The excess inventory will be converted into USD, to give a better idea of the potential losses that the company is exposed to.

In terms of the acceptable levels for the measurement, it can be argued that the same process as for the DFC can be applied, where a deviation of 10% was deemed acceptable. However, because this KPI assesses the coverage over the next 3 months, rather than the number of days the stock can cover, and because any potential fluctuation is already considered in the system, any excess stock recorded will be considered a potential risk.

4.2.2 No forecast production

Based on observed data, there is another category of potential risks that need to be considered. Like the excess, no forecast is also related to the production process for the company. The significant difference is that the plan that was proposed for production did not include these products and were not identified beforehand. Hence, these are still manufactured and appear in the final total available inventory, adding to the possible risk of expiration. The problem detected with the non-forecasted SKUs is that there was no demand for those, and in some instances, those were given also a NOD (note of discontinuation), which implies that an SKU will not be further produced for different reasons. Thus, a dedicated measurement is defined by the researcher in the tool, to keep track of those instances. It is helpful for the business to first identify the productions in question and update their production planning as soon as possible, as it will also help avoid the excessive disposal that is the core problem that currently the company has. No planned production is an easy-to-maintain performance indicator, as it flags SKUs which are on the actual list of production, but do not appear in the frozen forecast. In the background of the tool, if an SKU is in this scenario, a Boolean process will trigger and the values in cases and USD will appear in the dashboard.

4.2.3 Production vs Actual Sales

This KPI is introduced to keep track of the performance of the sales forecasted vs the production that took place. Having this overview is beneficial for the business, as it provides a clear picture of whether the assumptions of the sales were accurate, and the degree of accuracy, and helps improve the planning process in further years. High degrees of deviations from the forecast by the actual sales can translate into a faulty picture provided by the financial department. The importance of having an accurate sales forecast was also underlined by (Zallocco et al., 2009) and (Mentzer et al., n.d.), as a mark of an efficient process for both the management team and their employees.

Based on scientific literature, there are multiple ways of assessing forecast accuracy. The most common three methods are Mean Absolute Deviation, Mean Square Error (or short MSE) and Mean Absolute Percentage Error (or MAPE) (Basson et al., 2019). Based on industry practices, the method selected to assess forecast accuracy in the built tool was MAPE. The justification behind this choice is that MAPE translates the given deviation of the forecast in percentages and is easier to estimate by multiple actors who might not know the significance of the measure. Moreover, the method is optimal for checking large amounts of data, because of its scale sensitivity (Basson et al., 2019). The standard formula of MAPE is:

$$MAPE\ score = \left\{\frac{1}{n}\sum\frac{|Actual\ sales - Forecasted\ sales|}{|Actual\ Sales|}\right\} * 100 \qquad (6)$$

where n represents the number of cycles over which the error was measured

To compare the performance of the forecast given by demand planning, some benchmarks need to be defined. A “good score” can vary based on multiple attributes, such as the market for which the computation is applied (Basson et al., 2019). The common opinion around thresholds for MAPE is that a score under 5% indicates an accurate forecast, between 5% and 10% an acceptably accurate, 10% to 25% points at a low, but somewhat reliable forecast, and anything above 25% is viewed as unreliable and inaccurate forecast. The mentioned thresholds do not have enough scientific evidence to be fully backed, however, these estimations may be useful when assessing the MAPE score for the used forecast.

4.2.4 Actual Production vs Planned Production

As its name states, this KPI is meant to provide an overview of the difference between the planned production and production that took place for each factory on a weekly level, to keep track of how the inventory increase over a small period. From the weekly measuring, it is easier to move towards a monthly one, or even a yearly one, to compare changes between similar periods.

(Mentzer et al., n.d.) adds that “because logistics is responsible for moving products to specific locations, forecasts are needed at the product-by-location level”, highlighting that is important to study the factories where production takes place, as a source of diagnosing where the issue may come from. Hence, it is vital to have the necessary visibility of this measurement. As a formulation, the Plan to Production % (PTP) is simply dividing what was produced by what was planned, over the same period of a year, instead of considering two separate measures for underproduction and overproduction, as (Stevanoski et al., 2022) did:

$$PTP = \frac{inventory\ produced}{planned\ production} * 100 \qquad (7)$$

The KPI can be assessed on multiple levels, starting from a weekly level, up to monthly or yearly. Inside the tool, as the aim is to have a full-year picture, the whole inventory produced during a fiscal year is considered. As mentioned in previous subsections, the demand fluctuations which may occur can influence the planned production for that year. As the actual manufacturing should follow these changes as a response to the market demand, the planned production parameter is the final plan which was given a week prior, weekly, to the factory. Hence instead of assessing the adherence to the initial demand, in the dashboard the adherence to the most recent forecast.

The way of assessing the PTP level will be against the percentage the calculation gives. As discussed before and explained above, the production plan already considers all the potential changes in the demand. Thus, to avoid excess overstocking, the final score should not be above 100%. There may be instances where, due to business decisions, a weekly production can proceed to be above 100%, to anticipate certain upcoming events, or to make up a lower PTP score in previous weeks. This potential issue is tackled by considering the aggregation level of a full fiscal year (52 weeks). Hence, on this aggregation level, the plan to production score should be above 100%, to avoid potential overstocking (Stevanoski et al., 2022).

4.3 AHP selection process

The hierarchy of the performance KPIs (or observed effects) will be made by using the AHP weighting method. As mentioned in Chapter 3, there is specialized software meant for this, however, a manual framework for calculation will be preferred instead, because the complexity is not as high due to a small range of measures being selected (R. W. Saaty, 1987). The hierarchical selection starts by assigning scores to each of the KPIs, which were assessed together with the managing team and assigned accordingly. For this process, only the performance KPIs will be assessed, as the driver ones need to be included in the dashboard, because they may represent the root cause of the six performance KPIs selected in the previous subsection. Out of the six measures, only four of them will be included on the final performance list, based on the final weight, to satisfy the condition of having a small pool of KPIs to visually represent (Chae, 2009).

The selection process was designed to combine a scientific approach with the requirements of the supply planning team. To accommodate both, the previous list of KPIs will be used as input for a semi-structured interview. For the interview, a few members of the supply planning team were chosen to participate and to score their choices. The positions of the members selected are senior supply planning manager, supply planning manager, supply planner and supply planning lead. This selection of members ensures that the right requirements will be chosen, as well as having the possibility of receiving feedback throughout building the dashboard.

As such, using the previously designed list of KPIs as input, the task of the selected interviewees will be to score, individually, which KPI would best address and root cause the expiring inventory issue, the core problem for the research. The scores that will be used are 9 (extreme importance), 7 (high importance), 5 (moderate importance), 3 (low importance), and 1 (very low importance), with the rest of the numbers (8, 6, 4, 2) being transitional between each level of importance (R. W. Saaty, 1987). The average of the scores will be taken, and the result rounded to the closest value when needed. Assigning the scores will be made in a pairwise manner, for example, “Weekly Value at risk” versus “Fill rate”, where the former will be given a 5, and in the reverse pairwise comparison the “Fill rate” will receive a 1/5 importance in the same correlation.

One task of the researcher will be to check the validity of the weighting process, meaning there was not a high degree of subjectivity (R. W. Saaty, 1987). Hence, a consistency ratio needs to be calculated after the results are computed. After calculating the priority weights, the process of obtaining the consistency ratio will be described.

When building the matrix (Figure 5), its main diagonal needs to be 1 (highlighted in blue) and it will be filled in row by row with the weights. This is because when assessing each one of the KPIs in a pairwise manner, when the comparison will be made against the same KPI (for example “Fill rate” vs Fill rate” in the matrix) it needs to automatically default to the weight 1. The first step is to normalize the columns, such as the summation per each column is 1. This is done by first calculating the SUM of the COLUMNS row for each column KPI (Figure 5).

KPIs	Weekly Value at risk	DFC	Blocked Stock	Previous period disposed amount	Fill rate	Inventory turnover
Weekly Value at risk	1,00	5,00	5,00	6,00	9,00	5,00
DFC	0,20	1,00	2,00	2,00	5,00	1,00
Blocked Stock	0,20	0,50	1,00	5,00	6,00	4,00
Previous period disposed stock	0,17	0,50	0,20	1,00	2,00	2,00
Fill rate	0,11	0,20	0,17	0,50	1,00	1,00
Inventory turnover	0,20	1,00	0,25	0,50	1,00	1,00
SUM of COLUMNS	1,88	8,20	8,62	15,00	24,00	14,00

Figure 5: Step 1 AHP

The next step is to divide each cell of the columns by the corresponding SUM of COLUMNS. After the normalization, the sum of each column KPI should be 1 (Figure 6).

KPIs	Weekly Value at risk	DFC	Blocked Stock	Previous period disposed amount	Fill rate	Inventory turnover
Weekly Value at risk	0,53	0,61	0,58	0,40	0,38	0,36
DFC	0,11	0,12	0,23	0,13	0,21	0,07
Blocked Stock	0,11	0,06	0,12	0,33	0,25	0,29
Previous period disposed amount	0,09	0,06	0,02	0,07	0,08	0,14
Fill rate	0,06	0,02	0,02	0,03	0,04	0,07
Inventory turnover	0,11	0,12	0,03	0,03	0,04	0,07
CHECK SUM AFTER NORMALIZATI	1,00	1,00	1,00	1,00	1,00	1,00

Figure 6: Step 2 AHP

Finally, from the normalized matrix (Figure 6), the Final priority weight is calculated by taking the arithmetic mean of each row (Figure 7). These weights also exclude the last two scoring KPIs, which based on the results are "Fill rate" and "Inventory turnover".

Final priority weight
0,48
0,15
0,19
0,08
0,04
0,07

Figure 7: Final step AHP

Connecting back to a previous remark, the assigned scores need to be validated in terms of consistency. To validate whether the results were correct and whether there was not a high degree of subjectivity, a consistency ratio needs to be calculated, meaning if the choices made were consistent enough throughout the participants. The first step is to obtain the priority vector using the geometric mean:

KPIs	Weekly Value at risk	DFC	Blocked Stock	Previous period disposed amount	Fill rate	Inventory turnover	GEOMETRIC MEAN PRIO VECTOR
Weekly Value at risk	1,00	5,00	5,00	6,00	9,00	5,00	4,34727682
DFC	0,20	1,00	2,00	2,00	5,00	1,00	1,25992105
Blocked Stock	0,20	0,50	1,00	5,00	6,00	4,00	1,513085749
Previous period disposed stoc	0,17	0,50	0,20	1,00	2,00	2,00	0,636773219
Fill rate	0,11	0,20	0,17	0,50	1,00	1,00	0,350429807
Inventory turnover	0,20	1,00	0,25	0,50	1,00	1,00	0,540741874
SUM of COLUMNS	1,88	8,20	8,62	15,00	24,00	14,00	

Figure 8: Consistency ratio AHP

The next step is to perform the matrix multiplication between the pairwise comparison matrix and the obtained geometric mean priority vector. After that, we obtain the Eigenvector by dividing the obtained matrix by the geometric mean priority vector:

Pairwise matrix*prio vector	Eigen Vector
27,89052777	6,415631883
8,721985263	6,92264429
10,46191407	6,91429027
4,076240393	6,40140048
2,196754217	6,26874247
3,717206142	6,87427093

Figure 9: Consistency ratio AHP

The next step is to calculate the consistency index, where the dimension of the Eigenvector is 6, with the formula:

$$Consistency\ index = \frac{Principal\ Eigen\ value - size\ of\ the\ Eigen\ vector}{size\ of\ the\ Eigen\ vector - 1} \quad (8)$$

The Principal eigenvalue is simply obtained by summing the values of the Eigenvector and dividing by its size.

The last step for calculating the Consistency ratio is to divide the Consistency index by a random index. According to (R. W. Saaty, 1987), the consistency index depends on the number of options someone is weighing. The corresponding random index for 6 options is 1,24. After the division, the consistency ratio needs to be less than or equal to 0,1 to pass the consistency check (R. W. Saaty, 1987).

Principal Eigen Value	6,63283005	Random index	1,24
Consistency Index	0,12656601	Consistency ratio	0,10207

Figure 10: Consistency ratio AHP

4.4 Chapter conclusions

Based on the research topic regarding the expiring inventory of the business, a dashboard in PowerBI will be developed, which will include a list of KPIs. Based on previous scientific works these indicators can be divided into two categories, performance, and drivers. The drivers will be used as possible root cause reasons of the performance KPIs, while the performance ones go through a selection process to limit the number of possible alternatives. Using the list of six initial KPIs as input for supply planning interviews, an AHP calculation is applied. The result leaves four KPIs to be added and designed in the PowerBI tool, which also satisfies the condition of (Chae, 2009) of reducing the number of key performance indicators that are presented in the tool. The indicators are Value at risk, Blocked stock, Days forward coverage and Previously disposed stock.

5 Analysis and Results

In this chapter, the aim is to analyze the results obtained after building the proposed tool from Chapter 4. Each KPI that was selected for the tool will come with its separate set of results, depending on the level of aggregation and connection to the other KPIs, as well as a small section concerning the root cause analysis of some of the issues observed during the results analysis. Once the results are presented, a final section where a potential example that occurred during the analysis will be used as an example of the functionality of the tool. By using the example, the researcher can simultaneously also answer the final sub-research question posed at the beginning of the study, namely *"How to perform a conclusive analysis on product performance?"*.

5.1 Performance KPIs results

5.1.1 Value at Risk

The starting point of the checks for the Value at Risk will be to look into the available risk buckets that were loaded in the tool. Because the immediate risk is represented by the 0-30 days bucket, this will also represent the starting point. Based on the filters built in, a further layer for the comparison can be checked in terms of the year when the values were recorded. This way, a pattern can be recognized, where a country or product category represents a high risk, but was also recorded in the past as it created issues in terms of expiring stock.

0-30 risk bucket and 30-61 risk bucket

The top 4 regions with imminent risk in 2023 are UKI, Italy, Iberia and GAS, making up to 82% of the total quantity that is at risk, although those are only half of the countries that are being used in the tool. For the year 2022, during the same period in time, the two biggest offenders were also UKI and Italy, those two combined producing 50% of the total quantity at risk, whereas in 2023 the number was 62%. Worth mentioning is that during the same period of the year, in 2023 Company X had an increase in quantity at risk of 72% compared to 2022.

By diving one level lower in 2023, into the category of products that contribute to this risk, it is observed that "Category C" and "Category M" are the ones having the biggest problem, producing 18,9% and 17%, respectively. Putting it into perspective, 23 product categories are added into the tool, from the portfolio. By cross-checking the countries and product categories in the same view, the two categories are part of Company X's portfolio for the same 2 regions, UKI and Italy, which are the top offenders again. For "Category C", the quantity at risk for both UKI and Italy represents 14% of the risk, while "Category M" is only sold in the regions in question. For 2022, the main two categories as offenders were "Category C" and "Category I" (which was also present as a top 3 offender in 2023, with 8,3%). For the previous year, both accumulated 28% of the total portfolio's quantity at risk, with "Category C" being again the top offender with 17,2%. For both categories, UKI represented again a top risk provider, whereas Italy had lower amounts compared to 2023. Even so, the cumulative risk that the two countries have recorded two years in a row promotes them as top candidates for further investigation. "Category C", "Category M" and "Category I" also provide the type of products for which further analysis can be performed.

Coincidentally or not, the top 2 regions for the second highest bucket of risk, 31-60, were again UKI and Italy, cementing the need to analyze further the portfolio of these 2 countries for potential outstanding risk. The two regions were top 2 in 2023 and 2022, with 59%, and 45% respectively, out of the total quantity at risk.

The product categories which bring most of the risk in 2023 are “Category M” (19,1%), “Category C” (18,9%) and “Category B” (10,8%), where again for the first two, UKI and Italy were the main offenders. In 2022, “Category B” (19,7%) and “Category C” (17,4%) were the main offenders again.

5.1.2 Blocked Stock

For the Blocked Stock KPI, there are multiple views integrated into the PowerBI tool, as it represents an important indicator to show towards the supply planning team, as revealed by the AHP weighting method. The choice was to present the blocked stock values per product category, country, and manufacturing site, as the unavailable inventory affects both the countries which want to sell the stock and ship it, as well as the factories producing them, as it reduces the inventory space in the warehouses.

For the production sites, a list of the top 10 factories was created, and filtered based on the number of cases of blocked inventory. One way of categorizing the factories is by the type of products they deliver. For the company’s portfolio for Europe, the division of factories is those that produce Type 1 and factories that produce Type 2 portfolio. Hence, the same general distinction will be used when assessing the manufacturing sites, as it is easier to dive afterwards into the type of products that are “more blocked” than the others. The factories that produce Type 1 and associated products represented 48% of the total quantity of inventory blocked (total of the 10 factories), the rest of 52% being associated with Type 2. Preliminary, this shows that there is not much difference between the type of products from the portfolios to focus on only one of them. However, looking at factories individually, the one in Factory 6 stands out as the top offender, with a high quantity of blocked inventory, making out 28% of the total, which is a considerable amount, and it is specialized in producing mainly the Type 2 of products from the portfolio. The second top offender is the factory in Factory 1, which constitutes 19% of the total blocked. In this case, the factory is specialized in Type 1 products.

In terms of the countries, the top offenders were graphically represented with a scatter chart (Figure 11), to assess each country against Total Inv blocked in USD (x-axis) and Total Blocked Stock in cases (y-axis). The size of the bubbles represents the potential risk of the blocked stock. This way, the decision-makers can see which countries hold the most value in both USD and cases and help them determine where the focus should be directed towards. For example, a country can perceive a low number of cases, but the value of those can be higher, increasing the risk of losses for the business, which should also be reflected in this dashboard. Simply looking at the two measurements individually did not provide enough feedback, so combining those was the preferred choice. The regions with both a high number of cases blocked, and high inventory value are BNLX, UKI and Italy. The summed blocked value in USD by the three represents 84% of the total. In Figure 11, BNLX and UKI represent the main offenders for this KPI, with both presenting potential high risks of creating extra losses for the business. Referring to the previous section, UKI and Italy were already top offenders for expiring goods, which amplifies the need of underlining and solving the blocked stock issue for these countries, as it can help reduce further the amounts lost. In the case of BNLX, this business unit did not appear as a top offender initially, however, this can be easily explained because the data for that KPI is divided between the Netherlands and Belgium, countries that together form the BNLX unit for the business. At a simple calculation, it is revealed that the two together also provide 13% of the total risk in the 0-30 bucket, as well as 11% in the 31-60 days bucket, both in 2023, meaning that BNLX as a whole is also worth considering when further analyzing the countries with portfolio issues.

At a product level, the products that have the highest level of blocked stock are mainly from the Type 2 portfolio. Out of the top 10 SKUs, six of them were part of this category. Coincidently or not, these products are manufactured in the Factory 6 facility, which supports the claim made before regarding the factories with the highest level of blocked stock, meaning that in the future, this product category is susceptible to risk losses if the inventory is not moved from blocked stock.

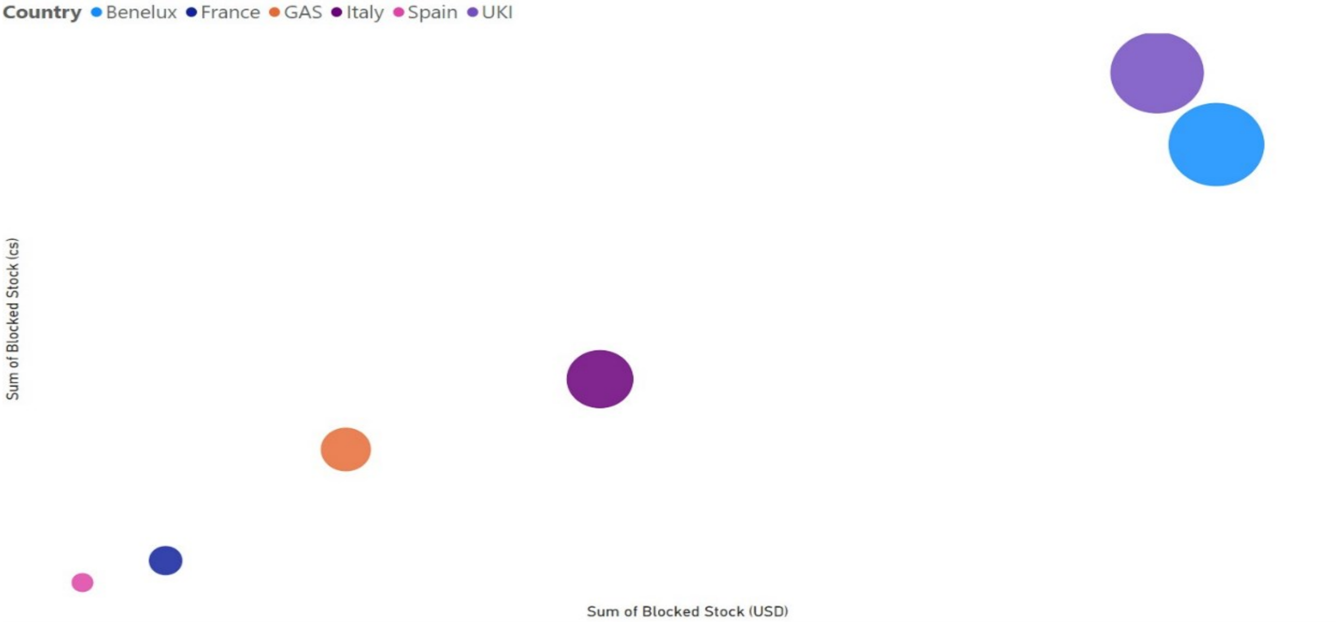

Figure 11: Blocked stock per region

5.1.3 Days Forward Coverage (DFC)

Days forward coverage matrix provides a per-category breakdown of the products' inventory which are above the set target. It simply shows the number of days that the current inventory would cover vs the number of days targeted. In practice, the target itself is not a static one and can vary per SKU depending on sales and supply. However, to ease and provide a simplistic, yet clear view, this KPI is displayed as a bar chart (Figure 12) that captures the weekly closing inventory level against a set forward coverage. This way, anybody can understand whether the business is producing too much or too little. Because the main topic of the project is to identify and analyze the possible risk losses, only the categories where the closing number is higher than the target will be considered and further discussed.

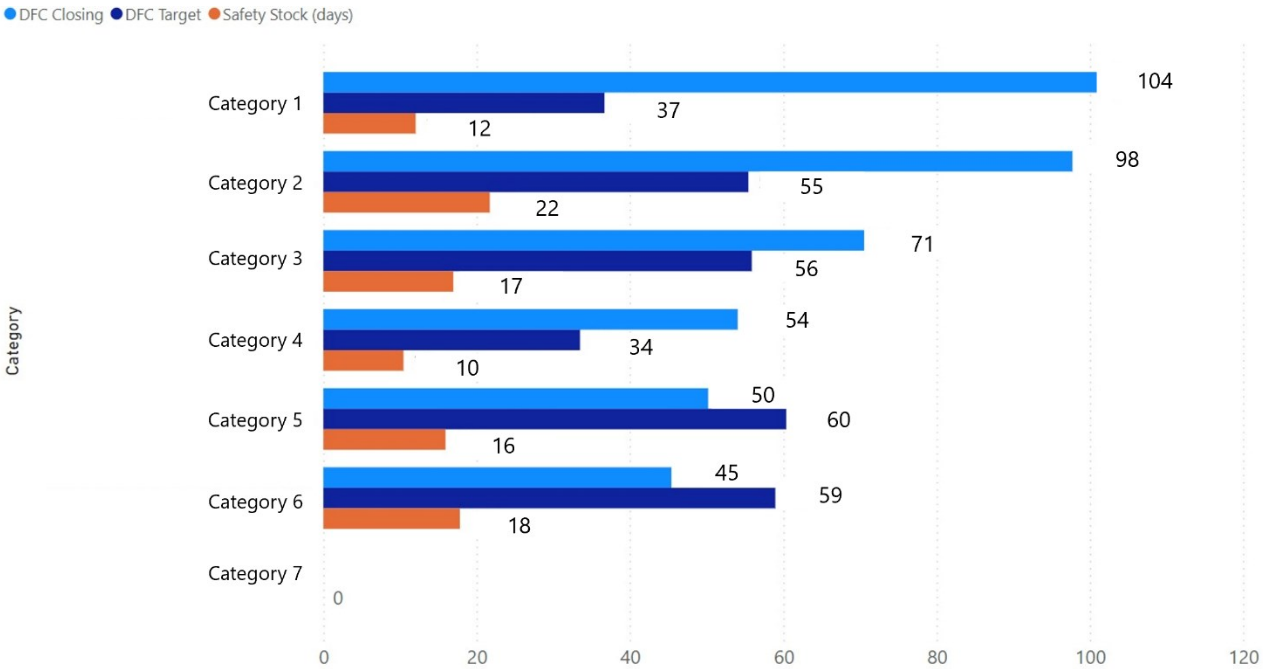

Figure 12: Days forward coverage per product category

The biggest discrepancy between closing and target days is for the "Category 1" category, with 181% more days over the target, followed by the "Category 2" category, with 78% extra coverage (Figure 12). This means that for those two categories, the business is massively overproducing inventory, increasing not only the potential loss risk due to the expiry of products but also the inventory on hand costs. This difference above in target is large enough to not be covered in the buffer defined in Chapter 4 of 10%, meaning that they are beyond reasonable coverage. Those numbers are in opposition to the bigger picture that the management team has available, as per the numbers recorded the closing DFC was smaller than the target DFC. The difference itself is not remarkable, as it shows a deviation of 2 days overall, which is negligible. However, if the two main offenders mentioned before are put in balance, the deviation can be substantial, but also it shows a lack of clarity from the business in two ways. First, it gives a wrong image of the coverage of the current stock and a decision can be made to increase the volumes being produced, and secondly, it takes up the resources that can be used to improve the coverage of other product categories which would need that, and represent a stronger selling point on the market, such as the "Category 6" one and increase the potential revenues.

5.1.4 Previously disposed stock

Quantity expired represents the amount of inventory that needs to be disposed of by the business due to passing the expiration date and cannot be sold anymore due to regulations (but also common sense). Hence, the abbreviation of P-BBE stands for Past Best Before Expiration date. The performance indicator itself is useful to show the historical amounts that had to be disposed of and keep track of what the business needs to throw away. Past and present data can give enough information to look at the particular products that are not selling well enough to be depleted from the warehouses, but also countries that over forecast or factories overproducing. If a single SKU or a particular product category appears multiple times throughout different years, then perhaps it is worth analyzing further, and the same applies to countries or manufacturing sites.

At the highest level, Company X doubled the amount of P-BBE quantity that had to be disposed of from 2022 to 2023, which may imply that either the forecast accuracy was low or that they overproduced way beyond normal levels. Looking at the volumes alone, this increase can be attributed to UKI and Nordics, and less to the other regions. The difference in the total quantity from 2022 to 2023 is almost the same as the delta between UKI and Nordics together from one year to another. Hence, in 2023 the top offender region was UKI with 50% of the quantity out of the disposed one, followed by Nordics region with 23%, GAS with 8% and BNLX with 6%. The same countries were also present in 2022, where the main malefactor was again UKI with 46% out of the total disposed quantity. Other notable ones were BNLX with 13%, GAS with 11% and Nordics with 9%. The most surprising increase is the one for Nordics. The amounts disposed have a considerable increase, especially for a region that does not have a high market value for the business. The Nordics case may be worth analyzing later during the root cause analysis, to understand what the reason behind it is and if in the future it can be identified in time for other countries as well. Another region worth mentioning based on the quantities is BNLX. Although it had 13% in 2022 and 6% in 2023, the actual volumes that were disposed of were not decreasing and stayed somewhat similar. The difference in percentages might be due to the huge jump in the total quantity that was mainly driven by UKI and Nordics.

Some of the categories which had the biggest inventory disposed in 2023 were "Category C", "Category B" and "Category I", with the first 2 being top offenders with around 14% each. The same three categories were also top offenders in 2022, where "Category C" had 18%, "Category I" 14% (whereas it had 11% in 2023), and "Category B" 11%. Despite the order being different, the amounts represent important losses that Company X saw in their Type 1 portfolio. Although most of the sales and revenues come through this line of business, the products that had to be destroyed represent opportunities lost in terms of sales, but also for their environmental commitments to reduce waste.

5.2 Driver KPIs results

5.2.1 Excess inventory

Excess inventory as a KPI aims to keep track of the total quantity and value of the inventory overproduced for each of the regions and for all the factories. By having this view, the company can keep track of all the additional volumes available and what is the potential risk of having those left in the warehouses. To some extent, it is a more general view that can include the Blocked Stock and Days Forward Coverage. Hence, the connection between these is for the bigger, more general overview (in this case the Excess) to have 2 additional, more detailed views that can explain the incorrect levels seen.

Excess production by its nature implies that at one or more points in time, the factories generated more stock, above a set target, increasing with no need for the available stock. The same assumption can be made also for the DFC indicator, which also shows the if the day coverage is above, below or on target. Hence, if in both cases the targets are set correctly to show acceptable levels, they should give the same result: the categories for which there is an excess of inventory. However, based on the graphical representation of the two (Figure 13 for Excess production and Figure 12 for DFC), it is concluded that this is not the case. The Excess inventory graphical representation shows that the biggest extra production occurred for “Category 6”, whereas this category appeared to be below target in terms of the days' coverage (Figure 13). Being above target for one should also mean being above for the other unless the corresponding levels are set incorrectly. The highest coverage in days SKU was lower in the list of excess production, which emphasizes the problem of incorrectly set targets. In practice, while not perfect, both KPIs should tell the same story: having an excess stock, that covers extra days in the future. This implies that adjustments should be made to one of the levels, or both, to better reflect the real thresholds that the company wants to have in place. One starting point for the management team should be to reflect whether the excess in cases and USD is firstly set according to the requirements. This will give them the needed visibility to understand when there is a risk of overproducing and where there are opportunities to improve. The Day's coverage should fall to a secondary plan, as this one is heavily dependent on the upcoming demand and can heavily fluctuate from one month to another. For example, if the sales perform worse in a month, the target will be set dynamically lower, but good sales should raise the level higher to anticipate the incoming demand.

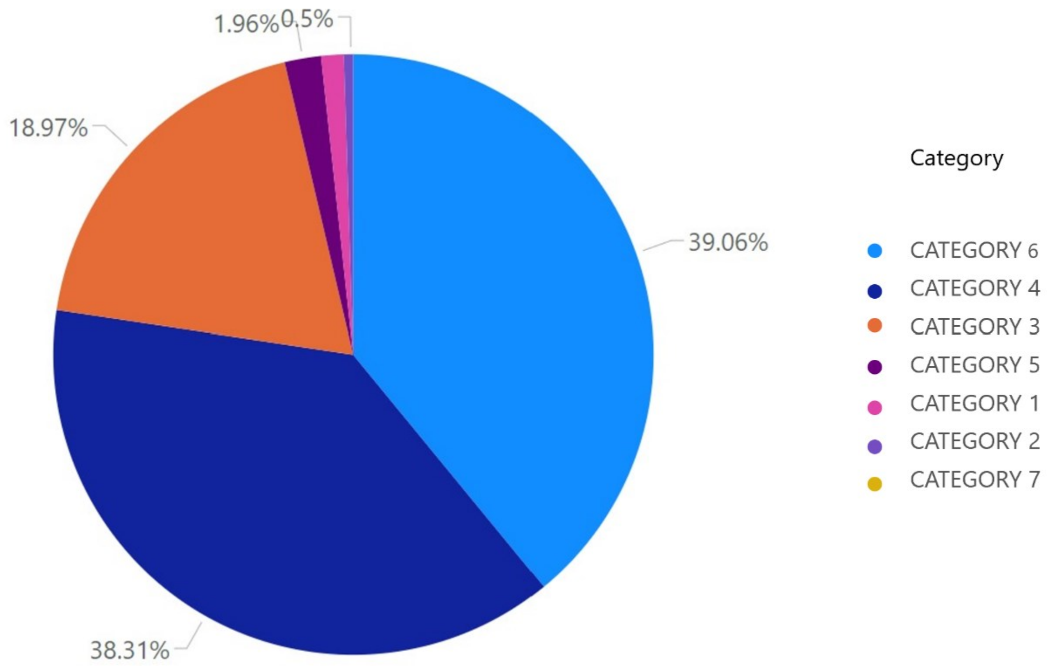

Figure 13: Excess production per product category

5.2.2 No forecast production

Similar to the excess inventory KPI, the No forecast production refers to excess, however, with the particularity that there was no forecast for the item manufactured (Figure 14). The difference is relevant because in this case, the produced SKU will never level the factory or warehouse, as there is no upcoming demand for it, and it will be lost stock. Because of the similarities to the Excess inventory KPI, it will be modelled the same way and integrated such that by pressing a button it will switch the data in the dashboard to show either No forecast or excess, depending on the wish of the user. This way, it will be easier for the user to use them almost simultaneously.

The performance indicator aims to give the decision-makers the needed view to prevent further increases in the stock of items without a forecast. If the system in place is planning future production which is under no circumstances needed, the supply planners can manually adjust this and stop it in time before it creates further losses. One solution for the already manufactured extra stock can be used in different markets for promotions, to boost potential sales, whenever it's possible. This way, the value will not be entirely lost and can help future increases in demand to raise the potential revenues of the company. If we switch to the view per region, this will reveal which countries can benefit from such promotions. Based on the discoveries of risk buckets analysis above, the most important countries which should consider this are the UKI and Italy. The same two can be found on the top of the list for no forecast inventory in USD, with significant value at risk, adding up to more than 60% of the total no forecast inventory (Figure 14).

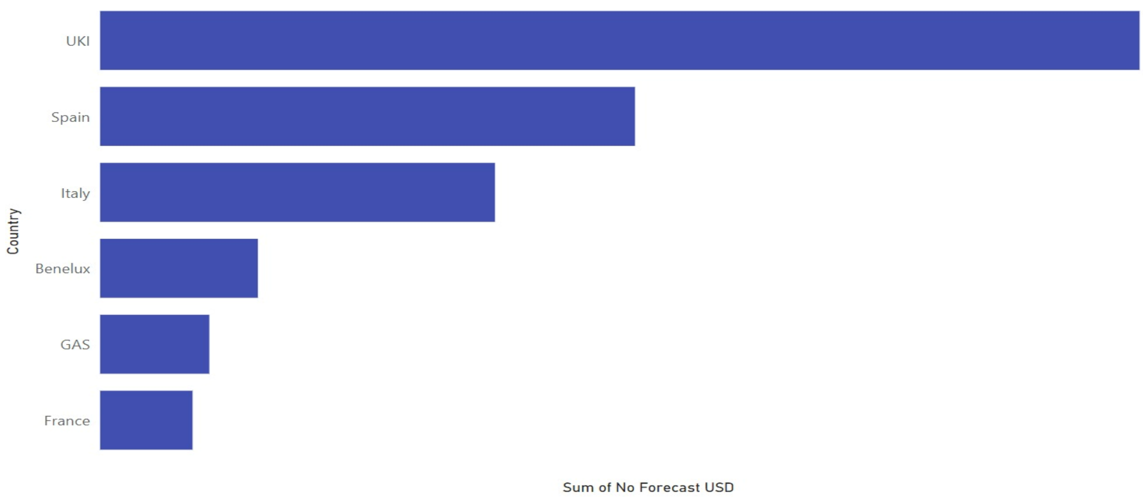

Figure 14: No forecast representation in USD per region

5.2.3 Plan to production (PTP)

Plan to production represents the indicator which keeps track of production performance in the company's factories. As mentioned before in Chapter 4, it simply divides the actual production by the planned one, to give the percentage of plan completion. A bad PTP, where the actuals were way below the proposed, translates into bad stock coverage and potential problems of completing the orders, while a good one keeps the inventory at a healthy state, where the stock flows harmoniously depending on the demand. However, when the actual production is considerably above the planned one, and there is no business decision to make to stock (increasing the stock above the target to anticipate certain events), then in that scenario, the factory has overproduced and there is extra stock available for certain items. To some extent, it is similar to the excess production, however, for this KPI, the historical data will be used to analyze the cause of the present expiry risk. For the historical data, for the current dashboard, the choice was to take the planned productions for 2022 and 2023, and two arbitrary points in time. One of the points in the timeline is in 2022, which shows the actual production in 2022, and the other is in 2023. This way we can have the background of manufacturing of the products that currently are in the list of risk. As the risk data that is present in the dashboard right now is from the first 12 weeks of 2023, the approximate date when they were produced should be in 2022, during the selected point in time. Thus, it is easier to pinpoint exactly where is the current expiration risk. The limitation of the data inserted lies in the fact that no countries can be displayed in the dashboard, because of the way the data was built initially. Hence, the assessments will be done based on factories and product categories.

The plan for production KPI (Figure 15, blue light bar versus dark blue one) will be represented mainly in a bar chart that shows comparatively the actuals and proposed production for all the main factories of Company X. Focusing on the main factories is one of the requests of the management team, as they are mostly interested in possible improvements that can be done to those, instead of the smaller, secondary ones. The biggest improvements in optimizing the volumes can be made by studying the primary manufacturing sites of the company. The PTP will also be presented at a product category level in a pie chart to drill down further. Based on the bigger picture, it can be observed between the planned production and what was actually produced, there is not much of a difference on an aggregated level, for all the factories together. This picture remains true when looking at individual factories, one by one. The biggest deviation is at around 2 million cases above the planned, which is still not big enough to explain the high volumes in the risk buckets. Hence, the problem should not lay on the production side, but most likely on the sales one, as there is evident data to support that Company X has overproduced massively.

5.2.4 Sales vs production

The production plan that is received by the factories and is in the planning system has its roots in the demand forecast that is prepared in advance by the demand planners. The numbers in there serve as the driver for the supply planning when creating the production plan for next year. Thus, when comparing the sales with the production, in reality, the sales forecast accuracy is being assessed. As described in Chapter 4, there are multiple methods and systems that calculate the accuracy of the forecast, however, for this KPI, actual sales versus forecasted ones will be used to assess how well the sales are performing. In the previous section, the production was compared to the plan, while for this KPI, the sales performance will be compared to the planned ones. For that, the very same points in time which were used previously for the PTP performance indicator will also be used in this section. The production plan for 2022 will be used as the demand forecast, as the latter represents the driving number for the former. The assumption made is that they are mirrored and either can be used, without missing anything critical.

The bar chart (Figure 15) presents the difference in cases between the planned production (light blue), the actual production that took place (dark blue) and the sales performance (purple), per factory. Having the additional parameter of actual production may help correctly evaluate the sales performance. Based on the plan to production indicator, it is already known that there was not a huge deviation from the plan on an aggregated view. However, if on a factory level, there was an overproduction, this can be caused by fluctuations in the latest demand forecast that was available, which should also appear in the sales evolution, as is the case for the Factory 4 manufacturing site.

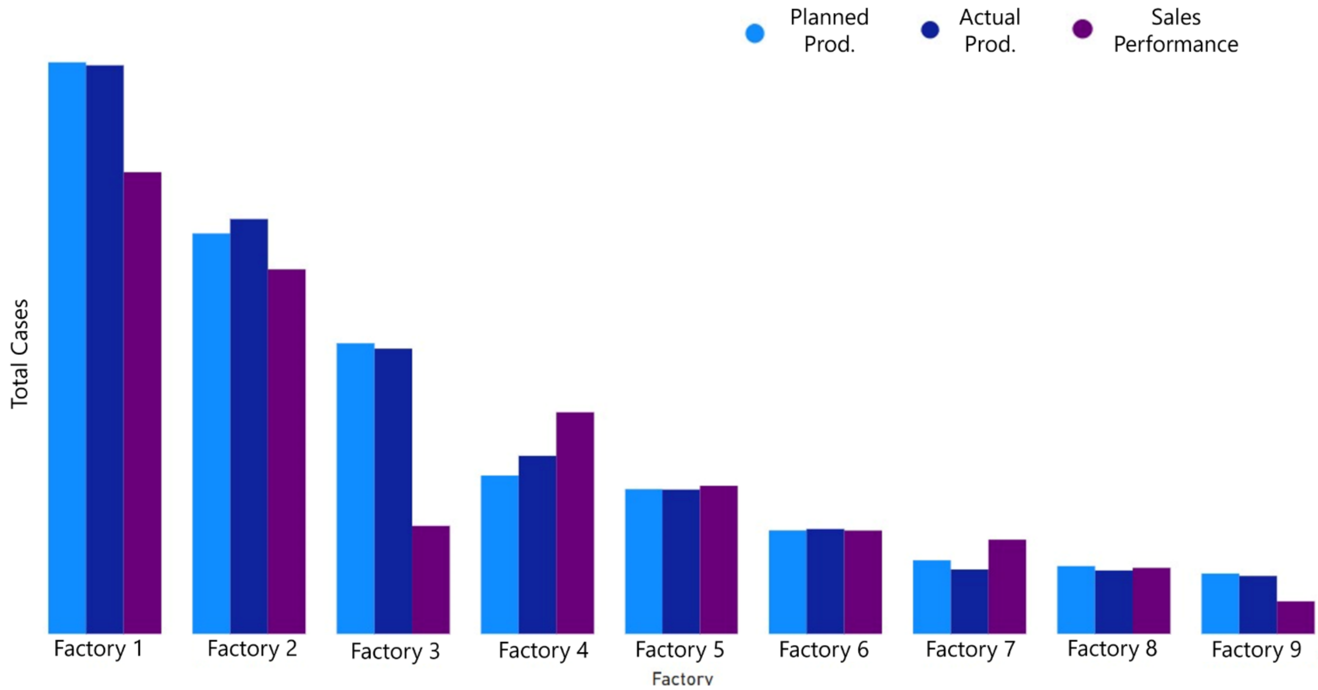

Figure 15: Sales performance against Production Levels

The evident conclusion that can be drawn from this view is that the sales performance of the company was not greatly forecasted. The manufacturing sites with higher production volumes are all underselling in 2023. Based on MAPE calculation, the biggest discrepancy comes from Factory 3, where only 39% of the volumes are being sold, and creates an excess of 15 million cases. The MAPE score for this manufacturing site is about 158%. The Factory 1 factory also creates an additional 10 million cases of excess because of underselling, however, its forecast accuracy error score is 24%, meaning that the forecast has a reasonable accuracy. In comparison, the smallest factory volume-wise, Factory 9, while it does not create a big impact like the other two mentioned, meaning about 2,5 million extra cases, the MAPE score was 91.5%, which based on the ranges established in Chapter 4 translates into an unreliable forecast. The total score of the company was 26%, which indicates that the forecast, while not accurate enough, can still provide a reasonable to follow for production. Besides the 3 factories mentioned, all the others had a good MAPE score, meaning that the forecasting issue is not a general one, but can be localized for some particular manufacturing sites.

The one concern that can be raised is whether the numbers forecasted by the demand planners include a bias. This bias would present as an extra percentage that is added on top of the volumes already forecasted and should be consistent throughout all factories. Hence, all the manufacturing sites would have the same percentage in the volumes forecasted. Analyzing the volumes for each one of the factories reveals that there is no potential bias included in the forecast. The potential bias value can vary between 2% and 61%, which contradicts the requirement of a constant added percentage. Hence, a bias was not included in the forecast.

5.2.5 Analysis of the final results and Root Cause

The starting point of the analysis is to find a reasonable explanation as to why such high volumes of inventory end up being close to expiry, making them unsellable to the retailers and provoking huge losses. The KPIs presented above are all part of the list of possible reasons for which this happens. As mentioned in Chapter 4, the list of KPIs was divided into two categories, Driver and Performance KPIs, to distinguish them better when analyzing the results. As stated before, the Performance measures are those related directly to the Risk Buckets that are being studied and serve as the detailed level of the dashboard, after which there are no additional data. In this layer, one can observe the immediate impact of the Drivers, such as past expiration amounts disposed of, days of coverage of the current stock, or blocked stock. Based on the observed information from the multiple views, a few re-occurring patterns were observed. First off, the main regions which were top offenders for the immediate risk, but also quantities disposed were Italy and UKI. The second one can be since it is the biggest European market, with a vast portfolio and high volumes being sold and being produced for it, however, the former represents a surprise, as the portfolio with the biggest market share is the Type 2 one, and for the company, the main one is Type 1, for which the highest amounts of inventory are produced. This pattern is still accurate when checking the Blocked stock inventory, proving that in the near future, the same two regions will produce a significant expiration risk impact.

For the Days coverage in days measurement, it was revealed that the target accuracy might be unreliable, considering it wants to express overstock and understock for a particular product category in days coverage. The difference in results between records reported for this measure and the Driver KPI Excess production may imply that one of those is set incorrectly. The assumption made is that the most probable one to be incorrect is the one for days. This is because measuring stock at such a granular level as days may lead to misleading information, as demand flows are dynamic and can lead to strange results when assessing at a daily level the stock remaining and the sales that took place. The most common industry practice, which the company also uses (besides the days) is to measure either weekly or monthly stock coverage.

The “Excess production” and “No Forecast production” KPIs start contouring the reason behind the risk buckets problem. The two Driver KPIs unveil that there is an excess of inventory available for all regions (Figure 16). UKI and Italy which were identified as a problem earlier, are part of the top three regions with excess stock, as shown in the bar chart.

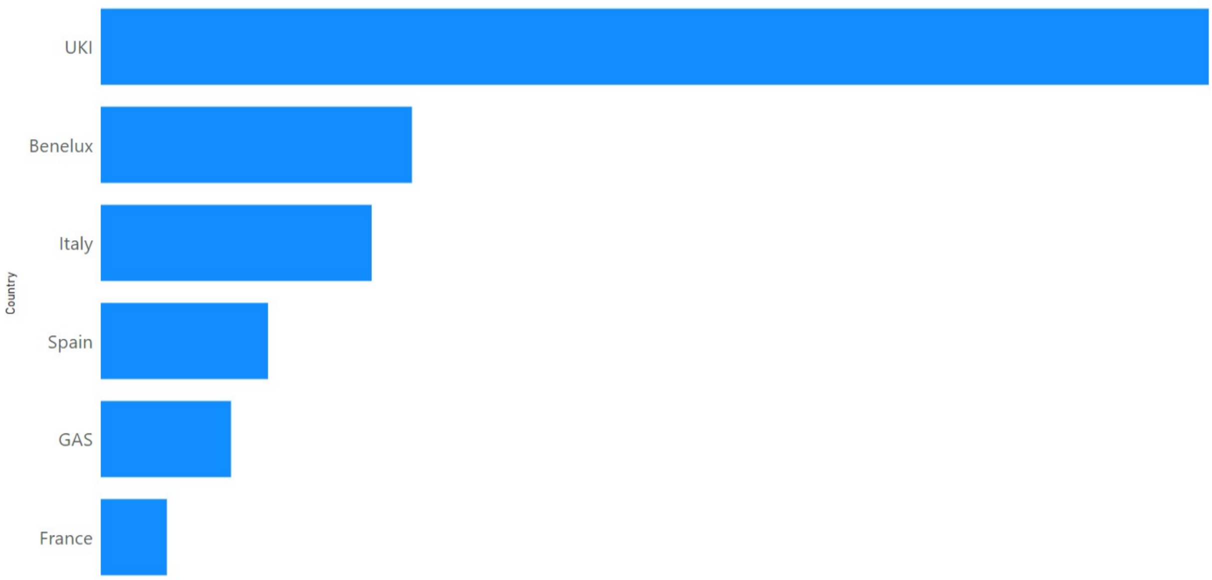

Figure 16: Excess production per regions

However, the nature of the excess still needs to be determined for them. Excess inventory can surface mainly because of two reasons in the case of Company X. Either the company produced more than it should have, or the sales performance was not in line with what was expected. Hence, the last two Driver measurements keep track of the plant performance and tries to determine the difference between sales and forecast. Based on the numbers displayed for them, the conclusion is that the excess nature does not relate to the production of the factories, as the difference between the proposed plans and actuals was smaller and cannot explain the high quantities that are at risk of expiring or already expired and were disposed of. The problems lay in the forecast made for the markets. The MAPE score of each factory shows that overall the forecast is not reliable enough and requires additional expertise and improvements. The deviations were substantial and disrupted heavily the supply chain by increasing the stock available. Furthermore, the “Excess Production” and “No Forecast Production” show what countries theoretically have an overproduction and connect the dots with the other two drives.

The product categories that are also placing a lot of quantity at risk of expiration are” Category C”, “Category M”, “Category B” and “Category I”. The already mentioned regions were present for each of the categories' list of top offenders. This is partially consistent also throughout the Driver KPIs. The “Category B” and “Category C” categories represent the main products that the business is selling in all markets. As such, because the volumes are high, it may cause excess inventory as well. “Category M” appears a potential risk, which is caused by a high volume of production in the main factory where those are created, against a relatively small demand. This will cause a lot of risk, especially in the future, as the market and demand for these type of products is dropping, making it a potential high risk that may appear further.

5.2.6 Tool testing

To test the feasibility of the KPIs and if they indeed provide a good way of checking the cause of historical risk from one of the buckets, the region Nordics was selected for testing. As Nordics represents another outlier in the analysis of Past Expiration Date KPI, but it did not represent a main market that can have huge volumes associated with it, it was the perfect offender of the list to check further. It was revealed that the quantity that had to be disposed of for this region was the second highest after UKI, in 2023. Thus, it proved a good example of root causing the abnormality and understanding of what happened. The first step is to identify the type of products that were disposed of in 2023 for this region, which can be easily observed from the pie chart created (Figure 17). The main three categories which had high volumes disposed of are revealed. However, this does not say enough about the cause, so an additional filter is necessary to remove the “noise” from the visual, meaning to focus on the most important categories and the factory where they were produced. Nordics not being a major market means that it does not have a direct primary plant which can be identified as the source of production. The data used for this visualization includes the identification code of the last warehouse/factory from which the SKUs were sent, meaning some additional digging needs to be done to understand which one it is. Because multiple product categories can be investigated, the choice was made to investigate the main offender, the “Category A” as it is not as common as “Category B” and “Category C”, although it had the biggest volume for Nordics. Based on the information provided by Company X’s supply planner team, the warehouse code which matches the filtering is one in The Netherlands. There are only two factories from NL that send their products there, and based on the fact that the product from the pie chart is part of Type 1 portfolio, it can be deduced that the primary production site is the one in Factory 1. Based on the volumes of “Category A” produced and sold for Factory 1, it can be observed that there is a gap of around 650K cases. This amount alone represents almost 60% of the total amount of disposed quantity for Nordics for this category alone and 16% of the total amount disposed into all portfolios of Nordics. The rest of 40% of “Category A” amounts stem from other, smaller factories and do not pose the main threat. Having this visibility in time to act, it would have saved lots of value for the company. Even so, having the ability to pinpoint in the past the main offenders and having them presented in multiple views still offers a valuable tool for the business to use.

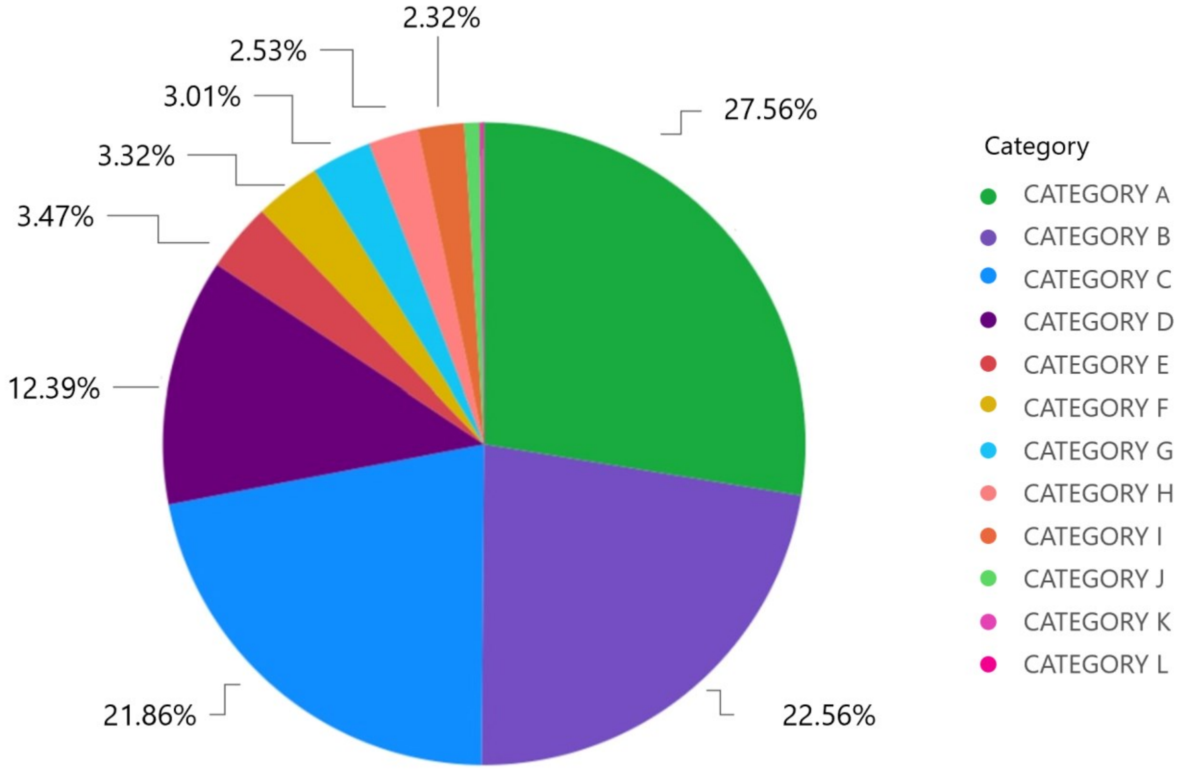

Figure 17: Excess Production of Product Categories, Noridics Region

5.3 Chapter conclusions

The main results of the key performance measures are assessed to arrive at the root cause of the core problem of the research, the excess inventory that ends up expiring. The main conclusion drawn from the analysis is that the inventory target levels may not be correctly set by the company, which means that it affects the potential stock levels that need to be kept to satisfy the demand.

The second conclusion drawn is that based on historical data collected, there is no excess production from the factory side, meaning that the deviations from the plan are minimal compared to the inventory at risk of expiring. Based on a MAPE assessment it was revealed that the main disruption comes from an inaccurate forecast provided by the demand planning department. Moreover, a final section presenting the capability of the tool on a scenario was presented, showing the potential root cause for one of the markets.

The final section helps answering the proposed sub-research question for this chapter, namely *"How to perform a conclusive analysis on product performance?"*. Based on the Nordics region example, an individual can identify the potential cause of the current expiration risk that can be observed, hence having a better understanding of how to determine which products are not performing as wished.

6 Conclusions and recommendations

6.1 Conclusions

The starting point of the research process was to find a suitable way of displaying inventory at risk of expiring. This was achieved by creating a PowerBI dashboard which includes suitable KPIs to keep track of both the stock at risk of expiring, but also similar measures that may influence it. After the creation of the tool and the analysis that followed it, a few final results and conclusions can be drawn.

Firstly, multiple KPIs revealed that a few markets were constantly showing problems in terms of stock that was at risk of expiring, but also already expired. Recorded data from 2022 and 2023 showed this is a trend, and the issues are only aggravating. From 2022 to 2023 the business recorded a 72% extra inventory risk, while for the same two years, the quantity that had to be disposed of doubled. The main regions that caused disruptions in terms of risk and losses were UKI and Italy, regions that were consistent throughout multiple aggregation levels. The main risk came from the product categories which were also the main offenders based on the analysis, such as “Category C”, “Category M” and “Category B”.

Secondly, it was revealed based on the MAPE forecast score that the root cause of the poor performance of multiple KPIs can be attributed to an inaccurate forecast. On an aggregated level, the manufacturing sites had a decent score of 26%, which positions it in a medium range, where the forecast cannot be considered accurate, but reliable enough to be used. However, on a local level, some factories presented huge deviations from the production plan, resulting in extra stock that ended up unused. This discovery is relevant for the business, as it gives the direction needed to improve the inventory performance.

Finally, the previous conclusion implies that on the production side, the company is not overproducing and is not deviating from the production plan when manufacturing the stock. This realization is important for the business, as it emphasizes that the verification in place for this process is working according to requirements, and, if needed, the company has the potential to produce what is needed, without considerable deviations and significant losses attributed to stock levels.

6.2 Future recommendations

Based on the results section of the paper, a few future actions can be recommended for the company. It is recognized that there might be more, however, those appear to be the most important ones. By applying them, it is believed that an immediate impact can be observed by both the supply planning team, but also other actors who are in contact with them.

Firstly, as revealed in Chapter 5, there are inconsistencies in the set-up of the target inventory, which became evident when assessing the Days forward coverage and Excess inventory KPIs on a factory level. It is still inconclusive which one of them presents the more accurate picture of the business. However, the starting point should be reviewed every quarter if the targets that are set up in the system are still valid and in harmony with the demand that flows. Once the review is finished, more accurate KPIs can provide a better understanding of reality.

Secondly, based on a MAPE analysis, it was identified that overproduction is not related to the production of the factories, but rather the discrepancy of the deviation from the forecast. An inaccurate forecast should not be the driving plan for the business, as it will always produce losses. While this action is not part of the responsibilities of the supply planning team, it is highly recommended that the action is brought to the attention of higher hierarchy actors and to be brought to the demand planning teams. Each improvement of the forecast can see tremendous results over a year. If the MAPE score was improved from 26% to 20%, that would translate into a reduction of up 20% of the total cases that had to be disposed of, which is a considerable improvement. Smaller MAPE score would further reduce the total quantity that would be disposed of. The main product categories that can benefit of a more accurate forecast are “Category C”, “Category B” and “Category M”. The last one is especially relevant as the future demands are dropping based market trends, putting in danger any overstocking scenarios for it. The main three regions which can benefit from an intervention in demand are UKI, BNLX and Italy, which based on historical data have a pattern of having huge risks that end up being disposed of in the end, causing significant losses to Company X

Finally, the last recommendation is regarding the reliability and visibility of the records. Throughout the design of the dashboard, multiple times the reliability of the data was put under question, as different sources presented different numbers that contradicted. While it is hard to have the ultimate source of truth, with consistent data maintenance, the errors in reporting can be reduced. In terms of visibility of the records, the company already plans to invest in a PowerBI reporting system. Thus, having full visibility over what records are already available will boost future efforts, as well as eliminate potential uncertainties over the available sources.

6.3 Limitations

Throughout the research and implementation, there were a few limitations which were observed by the researcher. Firstly, the nature of some of those were related to the duration and scope of the assignment. The time span was 10 weeks to research and implement the solution for Company X, while the scope of the assignment referred to building a useable tool for the business to help them have a better visibility of the supply chain losses associated with expiring inventory. It is recognized that a deeper dive can be performed in future inquires, but the scope was clearly defined to refer to a higher view, rather to a detailed one or only one isolated problem experienced by the problem owners.

Secondly, some limitations were associated with the resources made available by the company. Some of the datasets used required some preparation and clean up in order to be used. The master data where the SKUs and their details were matched were also not completely clear, which caused additional issues. This is because older SKUs were no longer active and could not be used properly in the checks. Hence, the total number of entries used for the dashboard was limited to data that could be verified and matched throughout multiple reports. Moreover, the starting point of the project which represented datasets containing information about expiring products was also limited in terms of the period recorded. The data made available was from 2020 to date, but considering the previous issue of SKUs not matching, it reduced the period which could be checked for.

Finally, due to sensitivity of the information used, not all available descriptions and results could have been displayed without anonymizing the information. However, the value of the research process is in the tool itself and the analysis that can be built based on it, whereas the numbers can be loaded can vary depending on the needs and constraints.

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8 Appendix

8.1 Graphical representations

8.1.1 Excess production description

[redacted]

Figure 18: Cause KPIs: No Forecast and Excess production

The KPI is presented in multiple ways. First, in terms of a pie chart that presents excess cases contribution as a percentage of the total per product category. Secondly, a bar chart showing current excess in USD per country, together with a table having the top 5 products for which excess is produced, together with their values in cases. And finally, a scorecard that summarizes the total amount of cases on the stock that are considered excess. All these views can be filtered based on the country in which they are sold, category, SKU number and factory. Additionally, a button is present to transition to the No forecast KPI, which has the same graphical representation, but other values present, and of course, other results.

8.1.2 Production planned, production actuals and sales performance

[redacted]

Figure 19: Cause KPIs: Sales vs Production vs Production Plan

For the graphical representation, a pie chart containing the difference between production and sales is shown, in terms of percentage and how each product category contributes to the difference. The supplement to this will be a scorecard that shows the current difference between what was produced and how much is forecasted to be sold by the year, as well as a gauge to visually show the same difference more clearly. All of these can be further filtered from the slicers with factories and categories.

The difference between the planned and the actual will be again shown numerically with a gauge to present how it scales in the graph but will also be included in a bar chart that shows both of planned and actual in the graph, broken down per manufacturing site.

8.1.3 Value at risk and Previously disposed inventory

[redacted]

Figure 20: Effect KPIs: Value at risk, inventory turnover ratio

The graphs include slicers (filtering options) for the product type, year when data was recorded, factory, risk bucket and period throughout the year (from week 1 to week 53). One point that needs to be emphasized is that the available data for 2023 is only for the first 12 weeks. Thus, any comparison based on recorded year needs to take in account this detail, otherwise inaccurate comparison can occur. The risk bucket slicer helps filtering the bucket that needs to be checked by the user. The Past BBE option allows to filter the items that have already expired, making this page of the dashboard part of the Previously disposed stock KPI. Hence, this page display two KPIs that are being checked in the dashboard.

Moreover, those graphs will show the Risk Evolution during periods of time per bucket, including a threshold or median to assess how much over or under the risk was then expected. A pie chart showing how the risk is divided between categories and by which number of cases they contribute to it during a certain period of time. Finally, a top 10 table presenting the main offenders and the value in USD will also be included, which will show different products, depending on the filters applied.

8.1.4 Blocked stock and Days forward coverage

[redacted]

Figure 21: Blocked Stock and DFC measures

This measurement can be filtered based on factory source, SKU number, category and market (country) in which is sold. The graphical representation will be a bar chart containing both the Closing and Target DFC, per product category, showing the difference in each of the categories of the coverage. The safety stock values will also be included in the graphical representation. Its role is to provide the minimum number of days the product category needs to have as coverage, to provide an indication of the current state of the inventory and potential gaps between levels. The graph can be filtered in more detail by selecting a particular SKU, which will provide the exact coverage vs what should be. The scorecard will present the numerical difference in days between Closing and Max.

The Blocked Stock visual based on P-TBBE values is represented in a bar chart, with the values in USD per year, while the complete Blocked Stock is represented in a top 5 table with their product description, SKU number and value blocked. Another Scatter Plot graph shows the number of cases blocked, against the Total inventory, per country. This view is useful for the decision maker to review the amounts produced that are unusable for each of the countries and can define easier interventions to prevent that. A final scorecard presents numerically the total number of cases blocked, depending on the filters applied, the same for the other views designed for this KPI.

8.1.5 Values that had to be disposed of between 2023 and 2022

[redacted]

Figure 22: Value lost due to expiring in the first 12 weeks of 2022

[redacted]

Figure 23: Value lost due to expiring in the first 12 weeks of 2023

In figures 21 and 22 the comparison between the values that had to be disposed of is presented. The top graph in Figure 21 shows the full year of 2022 in terms of value disposed, with the first 12 weeks (purple points) selected for proper analysis. The second graph of both figures indicates that there is a trend of quantity to be disposed of increasing from week 5. Moreover based on the value the total quantity of 2023 is bigger than 2022 (for the first 12 weeks in both years), emphasizing the current problem that the business has with stock being disposed of and the need for a solution.