UNIVERSIDADE CATÓLICA PORTUGUESA

The Influence of Business Intelligence on Decision-Making Processes Within An Organization

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Católica Porto Business School
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Final Work in Organizational Context presented to Universidade Católica Portuguesa to obtain the master's Degree in Management with a Specialization in Business Analytics

by

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Abstract

This thesis examines the transformative role of Business Intelligence (BI), specifically through the implementation of a Power BI dashboard, in optimizing decision-making processes within Amorim Cork, a leading cork processing company. In this digital age, as organizations grapple with high data volume, the need for efficient data analysis and actionable insights becomes paramount. This study, grounded in an internship experience, provides a deep insight into the deployment of a Power BI dashboard designed to streamline the analysis of production orders deviations. The research adopts an Action Research methodology, emphasizing a cyclic process of planning, acting, observing, and reflecting to foster practical organizational changes.

The findings underscore the significant impact of BI on organizational decision-making. The Power BI dashboard not only centralized data for improved accuracy and accessibility but also tailores it for user experience by allowing customization. This facilitated quicker, more informed decision-making across various levels of the organization. The study further illustrates the dashboard’s role in enhancing operational efficiency by automating data processes, thus reducing manual errors and ensuring data reliability.

This research contributes to the understanding of BI's strategic value in decision-making processes and highlights the necessity for continuous improvement and adaptation of BI tools to meet organizational needs.

Keywords: Business Intelligence, Decision-Making, Power BI.

Words: 8322

Resumo

Esta tese examina o papel transformador do Business Intelligence (BI), especificamente através da implementação de um relatório de controlo em Power BI, na otimização dos processos de tomada de decisão na Amorim Cork, uma empresa líder na transformação de cortiça. Nesta era digital, com crescente volume de dados, a necessidade de uma análise de dados eficiente e de conhecimentos accionáveis torna-se fundamental. Este estudo, baseado numa experiência de estágio, fornece uma visão aprofundada na implementação de um reltatório em Power BI concebido para agilizar a análise dos desvios das ordens de produção. A investigação adopta uma metodologia de action research, enfatizando um processo cíclico de planeamento, ação, observação e reflexão para promover mudanças organizacionais práticas.

Os resultados evidenciam o impacto significativo do BI na tomada de decisões organizacionais. O relatório não só centralizou os dados para melhorar a precisão e a acessibilidade dos dados, como também os adaptou à experiência do utilizador, permitindo a sua personalização. Isto facilitou a tomada de decisões mais rápidas e mais informadas em vários níveis da organização. O estudo ilustra ainda o papel do relatório no aumento da eficiência operacional através da automatização dos processos de dados, reduzindo assim os erros manuais e garantindo a fiabilidade dos dados.

A dissertação contribui para a compreensão do valor estratégico do BI nos processos de tomada de decisão e realça a necessidade de melhoria contínua e de adaptação das ferramentas de BI para satisfazer as necessidades organizacionais.

Palavras-Chave: Business Intelligence, Tomada de Decisão, Power BI.

Palavras: 8322

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First Chapter

1. Introduction

In the rapidly evolving landscape of organizational management, the strategic incorporation of Business Intelligence (BI) tools has become a pivotal element in enhancing decision-making processes. This thesis, developed during my internship at Amorim Cork, aims to investigate the transformative impact of BI, with a particular focus on the implementation of a Power BI dashboard to optimize decision-making within the organization.

Established in 1870 by António Alves Amorim, the company has grown to achieve global significance, serving clients across almost every continent and generating annual sales exceeding 1 billion euros. My integration into Amorim Cork's Business Intelligence team, as part of the Management Control department, provided a unique opportunity to delve deep into the challenges and opportunities presented by BI tools in a real-world corporate environment.

The primary objective of this thesis is to explore how BI tools, specifically through the deployment of a Power BI dashboard, can influence decision-making processes at various organizational levels. By examining the development and application of the dashboard designed to streamline the analysis of production orders deviations, this study aims to contribute to the broader understanding of BI's strategic value in enhancing organizational efficiency and decision-making capabilities. The research adopts a case study research and an Action Research methodology, reflecting on a cyclic process of planning, acting, observing, and reflecting to foster practical organizational changes.

Through this internship and subsequent thesis, we aim to shed light on the critical role of BI in modern organizational management, offering valuable insights for both academic research and practical application in business analytics.

1.1 Report Restructuring Goals

Since this thesis is presented as an internship report, its main objective is not to answer a specific research topic that emerges from gaps in the existing literature. To this end, in order simplify and speed up decision-making, the research aims to achieve the following objectives:

- Centralize and improve data accuracy in a single report.
- Facilitate data access across the organization.
- Customize dashboard design and user experience.

Since they previously accessed this data through several Excel files which required manual update of the data, this new report would considerably improve the speed of access to data while always being up to date.

1.2 Research Methodology

To accomplish the given goals Action Research will be followed as the methodology. This methodology was chosen due to its cyclical, reflective, and collaborative nature, making it highly effective for projects aimed at implementing practical changes within organizations.

The cyclical process of action research which encompasses planning, action, observation, and reflection, fosters ongoing improvements, and guarantees that advancements align with the needs of users.

For this case study, the model will be adapted to include three specific cycles: Planning and Preparation, Design Report and Reflection. This will guarantee there is an identification of the current challenges and set clear executable goals. In a final stage, this also allows the possibility to evaluate the collected data and pinpoint areas for future improvement.

The adaptable nature of the method allows making modifications resulting in immediate feedback and results, which was a crucial aspect when creating the report once it was required to meet the requirements of the users.

1.3 Dissertation Structure

The structure of this dissertation consists of six chapters. The current chapter, Chapter 1, establishes the context of this case study by presenting the motives of the reconstruction, and explaining the goals, approaches, and structure of the research.

The second chapter presents the fundamental theoretical foundations that are essential for comprehending the project such as Big Data and Business Intelligence tools.

The third chapter points in detail the project goals, provides a theoretical context of the chosen methodology and a brief overview is provided about the reasoning of the internship.

The fourth chapter provides a comprehensive examination of the original report's structure and identifies the main issues. It also describes what improvements were made, to later analyse how the old and new report would compare.

The fifth chapter presents how the new dashboard was perceived by its users, while going into detail on their feedback on several aspects of the visuals.

The sixth and final chapter highlights the accomplishments, summarises the key findings from all the work done, highlights the study's primary contributions to end users, and suggests more research or possible enhancements.

Second Chapter

2. Literature Review: Business Intelligence to Support Decision-Making Processes

This chapter is structured into four subchapters, each covering key topics pertinent to this dissertation. The first subchapter discusses Big Data and Business Intelligence, followed by an exploration of the role of Business Intelligence in Decision-Making. The following subchapter reviews the most frequently used tools, culminating with a focus on Power BI (PBI).

The purpose of this literature review is to draw connections between decision-making processes and the impact of big data on these decisions, while considering how business intelligence tools can improve decision-making capabilities.

2.1 Big Data and Business Intelligence

In the realm of modern business operations, Big Data has emerged as a revolutionary force, fundamentally altering the landscape of decision-making. The term "Big Data" encompasses an unprecedented volume of data amassed from various sources (Mayer-Schönberger and Cukier, 2013). This data is not only vast in quantity but diverse in type, rapidly generated, and variable in veracity, collectively known as the four Vs: Volume, Variety, Velocity, and Veracity (Cappa, 2021).

The "Volume" aspect of Big Data refers to the immense quantity of data generated by digital technologies and processes. This includes data from social networks, machine-to-machine communications, sensors, transactions, and much more (Sagiroglu & Sinanc, 2013)

'Variety' speaks to the wide array of data types and sources. This diversity includes everything from structured numeric data in traditional databases to unstructured text, emails, videos, audios, and financial transactions (McAfee et al., 2012).

'Velocity' refers to the speed at which data is generated, processed, and analysed. The rapid generation of data from sources as mobile devices and changing online platforms means that data becomes available almost instantaneously (De Mauro et al., 2015).

'Veracity' in Big Data pertains to the reliability and accuracy of data. Challenges related to veracity include biases, noise, and anomalies in data (Rubin & Lukoianova, 2013). Data veracity is crucial as the decisions made based on Big Data analytics are only as reliable as the data itself.

According to Elena (2011), the term Business Intelligence (BI) was introduced in 1958 by an IBM researcher called Hans Peter Luhn, who defined the term "business" as a set of activities carried out to achieve a goal, and the term "intelligence" as the ability to understand the interconnections in the facts presented, in order to guide action towards the desired goal (Luhn, 1958).

Since then, BI has continued to evolve and has become an essential tool for all companies, as it is capable of transforming raw data into useful and meaningful knowledge that aids decision-making (Niu et al., 2021). It aims to provide a complete picture of business operations so that the company's available capacities, market trends, patterns and opportunities can be identified (Negash, 2004)

2.2 Business Intelligence in Decision-Making

Applications of BI in decision-making go beyond data analysis, they also include establishing a data-driven culture in organizations. A decision-making environment based on facts and up-to-date information is fostered by this cultural shift, which emphasises the use of scientific evidence rather than intuition (Popovič, 2012). As a result, firms that use BI in their decision-making process see an increase in the precision of their choices, which boosts their overall operational effectiveness. (Kowalczyk, 2017).

The essence of BI in decision-making lies in its ability to aggregate, analyse, and present complex data in an accessible manner, thereby enhancing the quality and speed of decision-making processes across all levels of an organization (Watson & Wixom, 2010).

Strategic decisions, such as entering new markets or product innovation, are grounded in predictive analytics and market trends analysis, enabling leaders to anticipate future challenges and opportunities (Davenport, 2006). On a tactical level, BI is utilized by upper management and specialists, who focus on achieving specific objectives by leveraging detailed analytics and reporting features (Sandu, 2008).

Lastly, BI systems provide operational managers with real-time data, dashboards, and alerts, facilitating immediate decision-making to address operational issues and optimize day-to-day processes.

The influence of BI on decision-making extends beyond particular organizational levels. Rather, it is a flexible instrument that meets the information requirements of various organizational levels BI should therefore be used by all elements of the organization; at senior management level, it should act as an input for tactical and strategic decisions, while at lower levels, it should help with day-to-day work (Loshin, 2003).

2.3 Most Utilized Tools

Selecting the right BI tool is pivotal for an organization's success once this tool will determine how effectively an organization can respond to market changes and optimize operations. (Davenport & Harris, 2017)

Several factors influence the effectiveness of BI tools, including ease of use, integration capabilities, scalability, and the ability to support real-time analytics. Selecting a tool that matches the organization's technical infrastructure and business goals is essential for maximizing the benefits of BI. (Mikalef et al., 2018)

The alignment of BI tools with business strategy is essential and they should not only process data efficiently but also align with the strategic objectives of the organization, ensuring that the insights generated are relevant, actionable, and contribute to the overall success of the business (Kaplan & Norton, 1996).

The evolution of these tools over the years, reflect the growing need for more agile, user-friendly, and data-driven decision-making processes (Howson et al., 2018).

At the moment, cutting-edge technologies like machine learning and AI are revolutionizing business data analysis, and these rapid technological advancements are shaping the selection and utilization of BI tools (Bharadiya, 2018).

Microsoft Power BI is one of the leaders among these tools, once it has a comprehensive BI solution offering a range of tools for data preparation, analysis, and visualization. Its integration with Microsoft's ecosystem and user-friendly interface has contributed to its widespread adoption (Powel, 2017).

The following table analyses Power BI usability comparing with other BI tools:

BI Tool	**Usage Circumstances**	**Pros**	**Cons**
Microsoft Power BI	Integration with Microsoft products, ease of use	User-friendly, strong visualizations	Limited advanced analytics
Tableau	Complex visualizations, large datasets	Exceptional visualization, community support	Higher cost, steep learning curve
Qlik	In-memory processing, associative data modelling	Flexible, robust data integration	Resource-intensive, less intuitive UI
SAS Visual Analytics	Advanced analytics needs	Advanced analytics, predictive modelling	High cost, complexity
IBM Cognos Analytics	Enterprise-level reporting	Scalability, comprehensive reporting	Older UI, complexity

Table 1: BI Tools Comparison - retrieved from Power BI, Tableau, Qilk, SAS and IBM websites

Furthermore, the landscape of BI tools is continually evolving. The future of BI is likely to see increased integration of AI and more sophisticated predictive analytics. This evolution will further empower decision-making processes, making them more proactive rather than reactive (IBM, 2020).

2.4 Microsoft Power BI

Launched in 2015, Power BI has become a leading tool in the business intelligence community, offering a robust platform for data analysis and sharing insights (Microsoft, 2024).

BI's popularity among business intelligence tools can be attributed to its deep integration with Microsoft Office products and services, making it an ideal choice for organizations already using Microsoft products (Gartner, 2022). Its ability to connect to a wide array of data sources, both on-premises and in the cloud, allows users to easily aggregate data from multiple sources into a single coherent dataset for analysis and visualization (Rad et al., 2018).

One of its critical features of is its real-time dashboard updates, which allow business users to see up-to-date information without the need for manual refresh (Turley, 2017). This feature is particularly important for timely decision-making in fast-paced business environments.

Despite its strengths, Power BI faces challenges and limitations, particularly in scenarios involving extremely large datasets or highly complex data models, where performance can be an issue (Larson & Fryrear, 2018).

2.3.1 Dashboards

Power BI dashboards are a single page, often called canvas, that consolidates multiple visualizations into an interactive and unified interface. These dashboards are designed to provide users with an overview of the business's key metrics immediately. They are customizable and can include a wide range of visualization types, such as charts, graphs, and maps (Microsoft, 2024).

The design and functionality of Power BI dashboards are central to their effectiveness. Users can create and share dashboards that display visuals from various reports, each of which can be linked to different datasets. This versatility allows for the creation of comprehensive dashboards that can monitor key performance indicators (KPIs) across different aspects of the business in real-time (Turley, 2017).

Dashboards can be set to refresh automatically, ensuring that the latest data is always available. Users can interact with the visualizations to explore the data further, making dashboards not just a reporting tool but an interactive exploration tool (Microsoft, 2023).

Users can tailor dashboards to meet their specific needs, choosing which KPIs to monitor and how they are visualized. This level of customization ensures that different departments within an organization can focus on the metrics that are most relevant to their operations (Larson & Fryrear, 2016).

By consolidating critical business data into a single, accessible interface, they enable business leaders to make informed decisions quickly. The ability to see trends, anomalies, and patterns immediately allows for proactive rather than reactive decision-making (Provost & Fawcett, 2013).

Third Chapter

3. Methodology

The present chapter will outline the methodology used to throughout the report restructuring, building upon the theoretical framework established in the previous chapter. It is divided into three sections: the project objectives are detailed in subchapter 3.1, the context of the research is explored in subchapter 3.2, and a theoretical description of the methodology in subchapter 3.3.

3.1 Project Goals

The main aim of this dissertation is to leverage PBI as a tool to facilitate data interpretation and decision-making regarding production orders deviations. This will optimise the data gathering and processing operations, while also providing analytical tools to allow users to maximise the potential of the data, which was previously not easily accessible.

Given that this thesis is structured as a report from an internship, it does not focus on addressing a specific research question arising from gaps in the literature. To this end, with the purpose of facilitating quicker and more straightforward decision-making, the research sets out to accomplish the following objectives:

1. Centralize the data in a single platform.
2. Improve data autonomation and accuracy.
3. Facilitate data access across the organization.
4. Customize dashboard design and user experience.

The internship took place at Amorim Cork, which will be introduced in subchapter 3.2. At the moment, to analyse production deviations, controllers from different factories resorted to several Excel reports, which required manual update of the data. As so, in order to standardize the way all teams looked at the data, the company proposed to develop a single automated PBI report, where the data is accurate and serves every need.

3.2 Research Contextualization – Amorim Cork

Amorim Cork began a process of digital transformation in 2018, with the first step in this process being the implementation of the MES system, which allowed access to production data almost in real time. This made it possible to improve the quality of information, as well as to control and plan each stage of the production process in advance. The next step was to implement the SAP ERP system in order to integrate and manage all the business processes and thus improve data processing.

After this change, the company, aware of its potential and benefits, began to invest in BI. As such, the information is collected from the SAP ERP system into a standby database, where it is processed and prepared through ETL processes, then stored in a Data Warehouse, in a Microsoft Azure Cloud, where it feeds several OLAP cubes, and finally the information is made available through various applications, such as PBI and Excel. In these cubes, the data is divided into five different categories: Finance, Order to Cash, Purchase to Pay, Plan to Fulfill and Transportation. Although some of these categories contain duplicate information, this segregation of data allows employees to access only the information that is relevant to them, improving system performance and simplifying analysis.

When information needs to be added to the cubes, it is necessary to send a development request to Unipartner, which is the subcontractor responsible for

Amorim Cork's data architecture. This implies several disadvantages since, as an external company, it is not possible to control how long it will take them, for example, to add an indicator to the cubes, making it a very time-consuming process most of the time. In addition, given that this entity lacks specific insights of the business, the indicators developed often contain errors and need to be corrected later. All of this means that, in some circumstances, instead of sending a development request, it is preferable to resort to other alternatives.

As part of the ongoing digital transformation process, with the increase in the amount and flow of information, the company began to invest in BI tools that would make data analysis easier and more intuitive, in order to get the most out of it. Before the implementation of these tools, data control and analysis were carried out in Excel files. This practice has several disadvantages, such as the fact that it does not allow several people to access the document at the same time, the slow speed in data handling, and the difficulty of automating data entry.

Therefore, with the aim of centralizing information and providing more secure and unified analyses, the organization adopted the use of Microsoft Power BI from 2021 onwards, which is the software used to develop the project. Currently, the company already has numerous reports in PBI for various areas but, despite the heavy investment in BI tools, there is still frequent use of Excel, more specifically the creation of ad hoc Excel files, since new analysis needs are always arising which cannot be carried out directly, as there is still a lack of information and inconsistencies in the system.

3.3 Method

With the objective of achieving the goals proposed in subchapter 3.1, the methodological framework of this thesis is founded on an integration of a case study approach and Action Research methodology. This hybrid approach is tailored to deeply investigate the implementation of BI tools at Amorim Cork and assess their impact on organizational efficiency and decision-making processes.

A case study approach allows for an in-depth investigation into a specific, real-world context, providing rich insights into complex issues like the implementation and impact of BI in decision-making processes.

Amorim Cork, the world’s leader in cork processing, represents a pertinent case study for several reasons. Firstly, the extensive historical background and worldwide reach of the organization provide a significant context for examining the difficulties and potential of implementing BI. Secondly, the company's recent initiatives towards digital transformation, including the adoption of BI tools, reflect broader trends in the field of BI.

Complementing the case study, the Action Research methodology facilitates a dynamic exploration of BI's impact within Amorim Cork. This approach has been selected for constructing the Power BI Dashboard due to its iterative, reflective, and participatory nature, making it ideally suited for projects aiming to implement practical changes within organizations (Coghlan & Brannick, 2014).

This methodology is particularly beneficial in contexts where the goal is to improve and involve in the change process those who are experiencing it. The adaptability of action research allows for adjustments based on real-time feedback and outcomes, which is essential when developing a business intelligence tool that needs to be customized to the specific decision-making processes and informational needs of an organization (Kemmis, McTaggart, & Nixon, 2014).

The primary benefit of action research is its cyclical process of planning seen in Figure 1, acting, observing, and reflecting, which ensures continuous improvement and alignment with user requirements (Zuber-Skerritt, 2001).

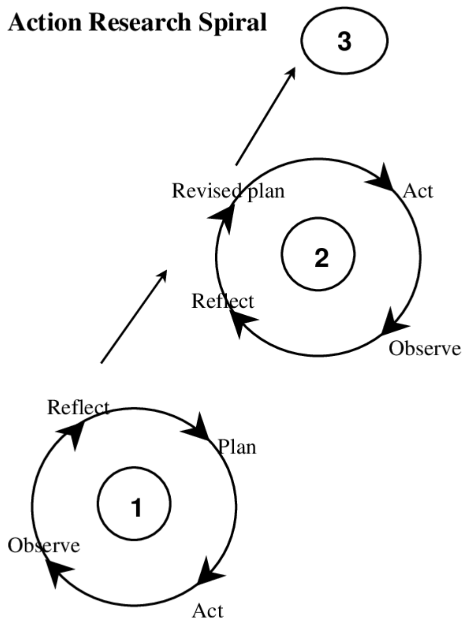

Figure 1: Action Research Cycles

This methodology encourages collaboration between researchers and participants, fostering a co-creation environment where knowledge and practice evolve together (Bradbury, 2015). Moreover, action research's iterative nature facilitates the identification and rectification of unforeseen issues (Stringer, 2013).

For the purpose of this project, it made sense to adapt the model, so it had three cycles, demonstrated in figure 2.

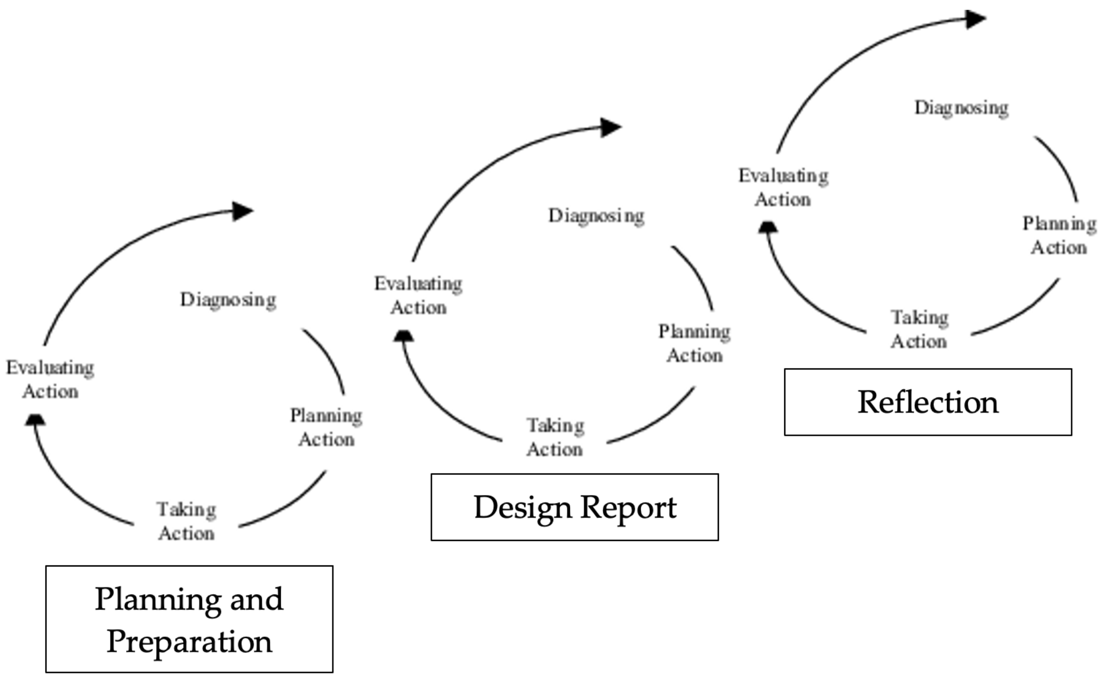

Figure 2: Action Research Adapted Model

The first cycle, Planning and Preparation, covers the identification of the problem within the organization's decision-making processes and delineates objectives for the Power BI Dashboard. This step requires extensive consultation with stakeholders to ensure the tool's development aligns with organizational needs (Greenwood & Levin, 2007).

In the second cycle, Design Report, the planned intervention is implemented, involving the actual design and development of the dashboard based on the requirements gathered in the first phase. It is crucial to maintain flexibility and adaptability during this stage to accommodate any necessary adjustments (Reason & Bradbury, 2008).

Lastly, the third cycle, Reflection, focuses in assessing the data collected during the first phase to evaluate the success of the intervention. This reflection leads to insights that form the basis for the next cycle of the action research process, ensuring it continues to evolve and improve in alignment with the organization's changing needs (McNiff, 2013).

Fourth Chapter

4. PowerBI Dashboard

This chapter explores the practical implementation of the Action Research approach used to construct the PBI report at Amorim Cork, building on the theoretical principles discussed in the previous chapter. It covers the process in detail, dividing it into three important stages, each with its own subchapter.

The first section, subchapter 4.1, conducts a comprehensive examination of the original report's structure and efficacy, by closely evaluating how it is being used and its capacity to answer the users' specific needs. This establishes a foundation in order to identify possible areas for improvement. Subchapter 4.2 delves into the improvements that were made, by describing the techniques used to put them into effect. This section not only explains the changes that were made, but also provides a justification for why they were necessary, presenting a deeper understanding of the reasoning behind each action. Finally, subchapter 4.3, presents a comparison between the original used method and the new report by demonstrating tangible improvements and thereby validating the effectiveness of the restructuring process.

It is important to note that this technique is flexible and adaptable, allowing for ongoing improvements. Even after moving through the cycles, there is still the possibility to go back and make more changes to earlier steps, ensuring continuous improvement throughout the process, not just at the start.

4.1 First Approach

During the development stage of the Power BI dashboard, the examination of production orders deviations was conducted using Excel. This approach was found to be extremely time-consuming, requiring frequent updates that not only required manual input from several sources but also made the process susceptible to human mistakes. The use of Excel demonstrated notable inefficiencies and showed the necessity for a automated approach to optimise the data analysis.

The implementation of this dashboard for aimed to significantly improve the decision-making process at different levels of the organization. This would cater to the specific requirements of management control teams at different factories, upper management, and factory floor staff. The dashboard needed to be suited to a wide range of users, thus it had to provide a high-level summary for making strategic decisions and a detailed perspective for improving operational efficiency and identifying issues.

To create this report, both financial and production OLAP cubes are going to be used. As shown in figure 3, these two datasets have several similarities, resulting in the presence of multiple duplicated tables that may potentially complicate the research process. As so, I had to compare the data present in both cubes and eliminate every duplicate table and retaining just the distinct and essential data. This is vital in order to guarantee that the dashboard could precisely provide information from both the finance and production aspects for the same industrial unit.

Figure 3: Merged Datasets Similarities

Within the current OLAP cubes utilised for the Power BI dashboard, there is a specific table intended for temporal analysis. However, this table merges months and years into an aggregated format, restricting the ability to do detailed time-based examinations. To address this limitation, I implemented a new table called "Mês Análise" and created a many-to-many relationship (Figure 4) between both tables, enabling the separation of data by month and year, providing a more detailed perspective of the data over time.

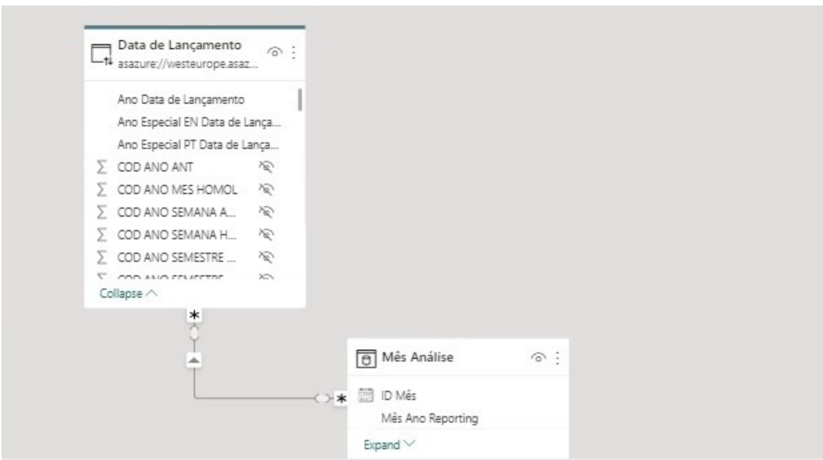

Figure 4: Relationship Visualization

Furthermore, in order to enable flexible comparisons across multiple time periods, both the financial and production cubes are supplied with tables that allow for easy modifications to various time ranges. These tables play a crucial role in facilitating different analysis, such as comparing current performance with year-to-date data.

4.2. Improvements

As previously sated the report is directed to multiple factories, so there is a need to identify and differentiate the profit centers associated with each one of them. For that purpose, shown in figure 5, I created a new table “Fábricas Centro de Lucro” and also established a many-to-many relationship with the already existing “Centro de Lucro” table.

	Fábrica	Centro de Lucro	ID Centro de Lucro	ID	CL Abreviado
1	Amorim Distribuição	AIPT-ADIS-Geral	1401201	4	Geral
2	Amorim Distribuição	AIPT-ADIS-Distribuição	1401202	4	Distribuição
3	Amorim Distribuição	AIPT-ADIS-Manutenção	1401203	4	Manutenção
4	Lamas	AIPT-LARN-Compra Rolhas SLINO	1403101	1	Compra Rolhas SLINO
5	Lamas	AIPT-LARN-Produção	1403201	1	Produção
6	Lamas	AIPT-LARN-Manutenção	1403202	1	Manutenção
7	Lamas	AIPT-LARN-Geral	1403203	1	Geral
8	CTC (Naturity)	AIPT-LARN-Naturity	1403204	9	LARN - Naturity
9	DS - Produção	AIPT-DSUI-Produção	1404201	2	Produção
10	DS - Trituração	AIPT-DSUI-Trituração	1404202	2	Trituração
11	DS - Produção	AIPT-DSUI-Geral	1404203	2	Geral
12	DS - Produção	AIPT-DSUI-Manutenção	1404204	2	Manutenção
13	EQ - Aparas	AIPT-EQUI-Aparas	1405201	3	Aparas
14	EQ - Distribuição	AIPT-EQUI-Distribuição	1405202	3	Distribuição
15	EQ - Trituração	AIPT-EQUI-Trituração	1405203	3	Trituração
16	EQ - Rolhas	AIPT-EQUI-Rolhas	1405204	3	Rolhas
17	EQ - Outros	AIPT-EQUI-Energia Equipar	1405205	3	Energia Equipar
18	EQ - Outros	AIPT-EQUI-Geral	1405206	3	Geral
19	EQ - Outros	AIPT-EQUI-Manutenção	1405207	3	Manutenção
20	PortoCork	AIPT-PTKN-Produção	1406201	5	Produção
21	PortoCork	AIPT-PTKN-Produção NDTECH	1406202	5	Produção NDTECH
22	PortoCork	AIPT-PTKN-Distribuição	1406203	5	Distribuição
23	PortoCork	AIPT-PTKN-Geral	1406204	5	Geral
24	PortoCork	AIPT-PTKN-Manutenção	1406205	5	Manutenção

Figure 5: Fábrica Centro de Lucro Columns

With the goal of providing a more comprehensive overview, a new table “Fábricas Mestre” (Figure 6) was also created, which combined several factories and associated them with different centers. This time, it was established a one-to-many relationship with the previous “Fábricas Centro de Lucro”.

	Filtro	Fábrica	Centro	ID Centro	ID
1	ATS 1	ATS 1	TSPT-Top Series Unit	2201	8
2	AD	Amorim Distribuição	AIPT-Amorim Distribuição	1401	4
3	CTC (Naturity)	CTC (Naturity)	AIPT- Cork Treatment Center	1403	9
4	CTC (XPUR)	CTC (XPUR)	AIPT- Cork Treatment Center	1418	11
5	CHK	ChampCork	CHPT-Champcork	4201	7
6	DS	DS - Produção	AIPT-De Sousa	1404	2
7	DS	DS - Trituração	AIPT-De Sousa	1404	2
8	Equipar	EQ - Aparas	AIPT-Equipar	1405	3
9	Equipar	EQ - Distribuição	AIPT-Equipar	1405	3
10	Equipar	EQ - Outros	AIPT-Equipar	1405	3
11	Equipar	EQ - Rolhas	AIPT-Equipar	1405	3
12	Equipar	EQ - Trituração	AIPT-Equipar	1405	3
13	Lamas	Lamas	AIPT-Lamas	1403	1
14	PTK	PortoCork	AIPT-Portocork	1406	5
15	VL	VL	AIPT-Vasconcelos & Lyncke	1407	6
16	ATS 2	ATS 2	TSPT-Top Series Unit 2	2202	10

Figure 6: Fábricas Mestre Columns

While developing all new necessary measures, DAX FORMATTER was an important online tool, by helping to organize and format code. All these measures can be seen in the following table:

Measure	**Description**
Vendas	CALCULATE ([Valor Eur/C1 Consolidado], 'Hierarquia de Contas' [Nome da Estrutura Hierarquia Contas] = "ERCI", 'Movimentos' [Código Centro de Lucro Parceiros Movimentos]="1400302" || 'Movimentos' [Código Centro de Lucro Parceiros Movimentos]="1400306"|| 'Movimentos' [Código Centro de Lucro Parceiros Movimentos] ="4200302" || 'Movimentos' [Código Centro de Lucro Parceiros Movimentos]="2200302" || | 'Movimentos' [Código Centro de Lucro Parceiros Movimentos]="2200304", 'Hierarquia de Contas' [Nive18PT Hierarquia Contas] = "Vendas para

	Cliente e Área Comercial" ||| 'Hierarquia de Contas' [Nivel8PT Hierarquia Contas] = "Vendas para Outras Áreas Industriais", 'Hierarquia Centro de Lucro' [Nivel1PT Hierarquia Centro de Lucro] = "Margens Corticeira Amorim")
Vendas LP	CALCULATE([Vendas], SAMEPERIODLASTYEAR('Data de Lançamento' [Data Data de Lançamento]))
Desvios	Desvios = calculate([Valor Eur/C1 Consolidado], 'Tipo de Valor' [Tipo de Valor] ="Real_Ajustamento", 'Area Funcional' [Código Area Funcional]="1100" || 'Area Funcional' [Código Area Funcional]="1400" || 'Area Funcional' [Código Area Funcional]="1300" || 'Area Funcional'[Código Area Funcional]="1500" || 'Area Funcional' [Código Area Funcional]="1200" || 'Area Funcional'[Código Area Funcional]="-1", 'Conta Plano Operacional' [Código da Conta Operacional]= "9202003100" || 'Conta Plano Operacional' [Código da Conta Operacional]="9202001100" || 'Conta Plano Operacional' [Código da Conta Operacional]="9202002100" || 'Conta Plano Operacional' [Código da Conta Openacional]="9202006000")
Desvios LP	CALCULATE([Desvios], SAMEPERIODLASTYEAR('Data de Lançamento' [Data Data de Lançamento]))
Saldo	- CALCULATE ([Valor Eur/C] Consolidado], 'Tipo de Valor' [Tipo de Valor] ="Real_Ajustamento", 'Area Funcional' [Código Area Funcional]="1100" || 'Area Funcional'[Código Area Funcional]="1400" || 'Area

	Funcional' [Código Area Funcional] ="1300" || 'Area Funcional' [Código Area Funcional]="1500" || 'Area Funcional' [Código Area Funcional]="1200" || 'Area Funcional'[Código Area Funcional]="-1", 'Hierarquia de Contas' [Nivel6PT Hierarquia Contas] = "Margem Bruta" , 'Hierarquia de Contas' [Nome da Estrutura Hierarquia Contas] = "ERCI")
Saldo LP	CALCULATE([Saldo], SAMEPERIODLASTYEAR('Data de Lançamento' [Data Data de Lançamento]))
Margem Bruta (Desvios)	CALCULATE ([Valor Eur/C1 Consolidado], 'Hierarquia de Contas'[Nome da Estrutura Hierarquia Contas]= "ERCI", 'Hierarquia de Contas' [Nive16PT Hierarquia Contas] = "Margem Bruta", 'Hierarquia Centro de Lucro' [Nivel1PT Hierarquia Centro de Lucro] = "Margens Corticeira Amorim")
Margem Bruta (Desvios) LP	CALCULATE ([Margem Bruta (Desvios)], SAMEPERIODLASTYEAR ('Data de Lançamento' [Data Data de Lançamento]))
% Margem Bruta	DIVIDE ([Desvios], CALCULATE([Custos], ALL ('Ordem' [Código Ordem])))
% Margem Bruta LP	CALCULATE ([% Margem Brutal, SAMEPERIODLASTYEAR('Data de Lançamento'[Data Data de Lançamento]))
MB	IF (CALCULATE ([Valor Emp/C1], 'Tipo de Analise Temporal' [Tipo de Análise Temporal]="Atual")=0, BLANK(), -CALCULATE([Valor Emp/C1],

	'Hierarquia de Contas'[Nivel6PT Hierarquia Contas] = "Margem Bruta" , 'Hierarquia de Contas'[Nome da Estrutura Hierarquia Contas] = "ERCI"))
MB/Qt	IF (HASONEVALUE (Material[Material PT]). [Margem Bruta (Desvios)]/- [Quantidade], BLANKO)
Custos	[Margem Bruta (Desvios)]-[Vendas]
Quantidade produzida (-1)	CALCULATE (-[Quantidade], 'Tipo de Movimento de Stock' [Código Tipo Movimento Stock]="101" || 'Tipo de Movimento de Stock' [Código Tipo Movimento Stock]= "102" || 'Tipo de Movimento de Stock' [Código Tipo Movimento Stock] [Código Tipo Movimento Stock]="101" || 'Tipo de Movimento de Stock'[Código Tipo Movimento Stock]="192" || 'Tipo de Movimento de Stock' [Código Tipo Movimento Stock] ="531" ||'Tipo de Movimento de Stock'[Código Tipo Movimento Stock]="532")
Quantidade Consumida (-1)	CALCULATE (-[Quantidade], 'Tipo de Movimento de Stock' [Código Tipo Movimento Stock]="261" ||'Tipo de Movimento de Stock' [Código Tipo Movimento Stock]="262")

Table 2: Developed Measures

In order to accommodate to the diverse viewpoints from the dashboard users, an important step was to incorporate multiple slicers to guarantee their ability to filter the visuals and data as needed. Furthermore, all these slicers had to be in sync hence avoiding any inconsistencies in values between different pages.

Also, to evaluate the factories' performance across the current and previous years, all visuals feature values for both periods. Tables have one column for each period and regarding the used charts, different colours were chosen to distinguish these periods and facilitate an easier understanding of the data.

The "Desvios às Ordens - Sumário" dashboard, figure 7, has been specifically designed for upper management to efficiently consolidate key data, providing a comprehensive overview of the operational well-being of the organisation. The four slicers - "Fábrica”,”Setor”, “Operação”, and “Ordem”—are essential for the system's operation. They provide a dynamic and customisable experience, enabling users to analyse data across many aspects of the company.

Figure 7: Summary Dashboard

The "Desvios às Ordens por Fábrica" component utilises a user-friendly bar graph to compare current deviations with past data. This visual comparison enables executives to identify and prioritise areas that need urgent attention or further investigation. The "Desvios às Ordens por Operação" section provides a detailed analysis of deviations in individual operations, enhancing the dashboard by uncovering efficiency variations within production processes.

The "Evolução Desvios às Ordens" line graph illustrates the temporal patterns of deviations. It not only shows changes during the year but also demonstrates performance in relation to the previous year.

An essential element of this dashboard is the "Custo da Venda" (Cost of Sales) function, which provides a concise representation of the financial consequences of sales operations. The "Desvios/Custo da Venda" (Deviations/Cost of Sales) indicator provides a clear and rapid insight into how operational efficiencies are connected to their financial implications.

The "Desvios às Ordens – Por Centro" page, presented in figure 9, enhances the analytical exploration that was began by the summary page. It maintains the same high level of detail while introducing new tools for controllers to navigate through order deviations. Focusing on specific profit centers, this page provides a detailed table that allows for a breakdown of deviations into operations, materials, and individual orders.

Figure 8: In-Depht Dashboard

Furthermore, the "Saldo por Operação" component adds an essential component to the research. It provides a bar chart that compares the data from the current year with the data from the previous year. This allows controllers to closely monitor operational success and financial well-being.

A new page dedicated to analysing gross margins was created, figure 9, after a meeting with a control management team. It was shown that the deviations analysis often happened together with reviews of gross margin metrics. This connection emphasis the necessity for a specific page that ensures comparisons may be carried out with more effectiveness and coherence.

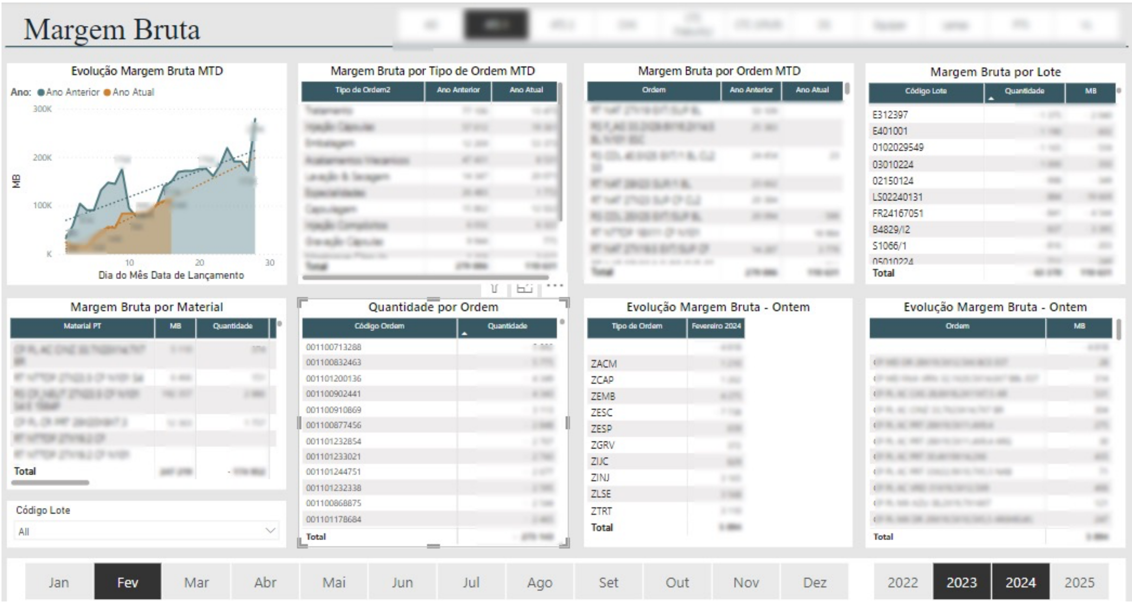

Figure 9: Gross Margin Dashboard

The page begins with a temporal analysis, featuring a line chart tracking Gross Margin Month-to-Date comparisons between the current and previous years. It also incorporates several tables that provide a detailed perspective of gross margins by order type and individual order and a batch-level breakdown revealing the profitability of individual batches and aiding in the quality control process as well as inventory management decisions.

4.3 Final Report

It is now essential to review the elements discussed in subchapter 4.1, incorporating the changes outlined in subchapter 4.2, in order to effectively validate improvements from the chosen method.

Looking at the first cycle, “Planning and Preparation”, several results might be drawn. In examining the organization's dependence on Excel, several key issues were identified that highlighted the need for a new approach.

The lack of standardization across teams and factories created inconsistencies in data handling, the process was time-consuming the manual nature of these reports made them highly susceptible to human errors. By leveraging PBI’s capabilities, the organization is now able to standardize reports across all teams and factories, ensuring consistency and comparability of data. Despite the complexity and potential discrepancies from using two datasets, the transition ensured that the data remained accurate and reliable.

The introduction of the new report is now directed to users from various levels of the organization, ensuring ensures that employees, from frontline workers to upper management, now have the tools to engage with data relevant to their roles and responsibilities in real-time.

The second cycle, “Design Report”, consisted mainly in the creation of a new dashboard from scratch. structured with three distinct pages, with the purpose centralizing the data location for ease of access and analysis.

To accommodate the diverse needs of the users, the dashboard was equipped with a total of nine filters, allowing for customization based on specific factors such as factories, centers, orders, operations, and time periods.

Unlike the previous Excel reports, which relied heavily on tables and often lacked visual appeal, the new dashboard utilized engaging and easily understandable visuals. This enhancement not only improved the user experience but also facilitated a more intuitive understanding of the data sets.

Finally, in the third and last cycle, Reflection, there was a review of the initial data collected and assessment on the efficacy of the intervention. It was found that the main objectives for the restructure were met, demonstrating significant improvements compared to the previous reports.

Fifth Chapter

5. Report Feedback

In the previous chapter, we explored the immediate benefits resulting from the restructuring process, emphasising the observable improvements made through the implementation of the new dashboard. This chapter now goes in depth on how the end-users evaluate the new report and its overall efficacy.

To evaluate the effectiveness of the newly implemented Power BI dashboard, a survey was conducted among a diverse group of users. This survey was designed to gather detailed feedback on the usability, functionality, and impact of the dashboard on the users' analytical tasks and decision-making processes. By employing a 7-point Likert scale, a method widely recognized for its ability to capture the intensity of respondents' feelings (Likert, 1932), ranging from 1, "Strongly Disagree", to 7, “Strongly Agree" it was possible to gather insights of the users’ satisfaction.

Out of the 11 controllers targeted by the study, 7 controllers responded to the survey, assessing the intuitiveness of the dashboard's interactive features, the appropriateness of its data visualization tools, the adaptability of the report to individual user needs, the efficacy of its comparative analysis functionalities, and the overall support it provides in the decision-making process.

The feedback on the "Intuitiveness and Utility of Interactive Elements" is highly positive. All the responses fall into the range of "Partially Agree" to "Strongly Agree," with 42.9% of users giving a rate of 7. This indicates that users find the interactive elements of the Power BI dashboard both intuitive and useful for their analysis.

For the "Appropriateness of Graphs and Tables for Data and Analysis," the responses indicate a strong positive reception among users. The responses are equal to the question, showing a high level of satisfaction with the visual data representation provided by the dashboard.

"Customizability of Data Visualizations" shows a strong positive response, with 57.1% of users "Strongly Agree" on the dashboard’s adaptability to their needs, highlighting a considerable degree of contentment with its customization options.

The results for the "Effectiveness of Comparative Analysis Features" also reveals predominantly positive perception among users, with 42.9% of responses rated as a 6, 28.6% as a 7 and the other 28.6% as a 5, showing general contentment but suggesting room for further improvements.

Finally, "Support in Decision-Making" indicates strong user approval of the PBI dashboard role in enhancing decision-making processes. 71.4% rated their satisfaction as a 6 signifying a high level of agreement with the dashboard's support capabilities. Additionally, 14.3% of users rated it with a 7 and the remaining 14.3% gave a rating of 5.

When asked about additional comments and recommendations, none of the controllers gave further suggestions, but the feedback obtained through the remaining survey indicates the dashboard has been well-received by its users and improved the decision-making process. This not only highlights the success of the restructuring process but also lays the groundwork for ongoing enhancements to ensure the dashboard continues to meet and exceed user expectations.

6. Conclusion

The goal of this dissertation is to leverage PBI as a tool to facilitate data interpretation and decision-making regarding production orders deviations. The report was developed for the company, Amorim Cork, where the internship took place.

6.1 Final Conclusions

All previously established goals were effectively achieved, directly contributing to the main purpose of leveraging PBI to facilitate data interpretation and decision-making regarding production orders deviations. Moreover, numerous other conclusions were reached after concluding the report.

The exploration into the realm of BI has revealed that its advantages extend far beyond from the initially perceived benefits. Outside the tangible and directly measurable benefits, BI offers a spectrum of advantages that, while harder to quantify or even unmeasurable, are equally critical to organizational success.

Another crucial insight gained is the importance of considering user profiles in the presentation of data. The efficiency of information delivery is significantly influenced by how well the data presentation is tailored to the diverse needs and preferences of its users.

The repetitive structure of the action research approach, characterized by its closely interconnected cycles, presents a difficulty in clearly categorizing the phases of the project. This feature highlights the active and ongoing improvement part of action research, which, although it makes it challenging to separate different phases, it significantly enhances its capacity to adjust as necessary.

6.2 Major Contributions

The project has markedly improved the accessibility of information. Previously, accessing and analysing data required navigating through complex Excel files but the introduction of the PBI dashboard has transformed this process, enabling users to easily access crucial information and make decisions.

The automation of previously manual processes represents a significant leap in operational efficiency. By reducing the need for manual data fixes and interventions, the dashboard minimizes the potential for human error.

The risk of accidental data alterations has been significantly mitigated. Ensuring the accuracy and reliability of the data reinforces trust in the information provided and the decisions made based on it.

The dashboard's arrangement of graphics and data visualization tools, allow end users to categorize information and focus on what’s most important more easily. It creates more room for meaningful information, making the report not just a tool for data representation but a powerful instrument for insight discovery.

6.3 Future Recommendations

Regarding BI procedures at Amorim Cork, I would suggest implementing several future practices.

It is essential to establish a culture of continuous improvement around the use of PBI dashboards involving not only periodic review and updates, but actively seeking and incorporating feedback from all users interacting with the report.

Despite the implementation of the current PBI dashboard, there remains a vast landscape of daily analyses still being conducted through Excel. It would be beneficial to identify and prioritize the main areas where this is happening and develop additional PBI reports.

The underutilization of existing PBI reports represents a wasteful opportunity for the organization. Efforts should be made to enforce the use of Power BI tools, ensuring that the resources invested in developing these reports translate into tangible benefits. This may involve a combination of training programs or awareness campaigns and by demonstrating the value and efficiency gains from using Power BI reports, along with providing the necessary support and incentives for adoption, the organization could overcome resistance to change and maximize the utility of its BI investments.

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