UNIVERSIDADE CATÓLICA PORTUGUESA

BI Tools to Monitor KPIs in Operations Management

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

by

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Resumo

Os key performance indicators são cruciais para a tomada de decisão e essenciais para quantificar a eficiência e eficácia da gestão das operações. Atualmente, é possível reunir grandes conjuntos de dados e estimativas que ajudam e apoiam a aquisição e cálculo dos KPIs. O Big Data permite às empresas utilizar os dados como um ativo estratégico para a tomada de decisão e criar valor através da análise e integração de dados em actividades estratégicas e operacionais.

Esta dissertação foca-se na melhoria da monitorização de um KPI através de ferramentas de BI. Este KPI é da Carglass Portugal e tem o objectivo de medir a conversão. A fim de melhorar a monitorização deste KPI, foi desenvolvido um R Script com o objectivo de melhorar o pre-processamento de dados e foi construído um dashboard em Power BI com o objectivo de melhorar a visualização e análise dos dados, e consequentemente a tomada de decisão.

A metodologia adoptada foi action-research estruturada em dois ciclos: Pre-processamento de dados e construção de um dashboard.

As principais conclusões desta investigação foram que, de facto, as ferramentas de BI com diferentes propósitos podem melhorar a eficiência nas tarefas diárias, mas também melhorar e acelerar a tomada de decisão.

Palavras-chave: Ferramentas de Business Intelligence, Key Performance Indicators, Pre-Processamento Dados , Dashboard, Visualização de Dados

Abstract

Key performance indicators are crucial for decision-making and essential to quantify the efficiency and effectiveness of operations management. Nowadays, provided by information technologies, it is possible to gather large sets of data and estimates that help and support the acquisition and calculation of KPIs. Big Data enables companies to use data as a strategic asset for decision-making and create value through data analysis and integration into strategic and operational activities.

This dissertation focusses on improving the monitorization of a KPI through BI tools. This KPI is from Carglass Portugal and has the goal of measuring conversion. In order to improve the monitorization of this KPI, an R Script was developed with the goal of improving data pre-processing and a Power BI dashboard was constructed with the aim of enhancing data visualization and data analysis, and consequently decision-making.

The methodology adopted was action-research structured in two cycles: Data Pre-Processing and Dashboard Construction.

The principal findings of this research conclude that, indeed, BI tools with different purposes can improve efficiency in daily tasks but also enhance and fasten decision-making.

Keywords: Business Intelligence Tools, Key Performance Indicators, Data Pre-Processing, Dashboard, Data Visualization

Words: 9405

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First Chapter

1. Introduction

The development of this dissertation was made under an internship at Carglass Portugal, which suggested an improvement in key performance indicators (KPIs) monitoring, taking into consideration the goal of improving data preparation for the KPI database and a dashboard development in Power BI to enhance data visualisation and, therefore, data analysis. The KPI in question is *Total Net Conversion* (TNC). The goal of the improving data preparation is to improve efficiency in the process of preparing the data to analyse TNC and, the goal of the dashboard in question is to analyse the conversion and, understand how the many variables and performance indicators are affecting the KPI overtime and at a certain period of analysis.

Carglass Portugal belongs to Belron Group which is the world's leader in glass repair, replacement, and recalibration. Carglass Portugal has an operations department which is divided in other departments. In this case, the Business Analytics role was included in the operations controlling team. Besides being a business intelligence job, the project was since the beginning hand to hand with the operations department and, at some point, paired with the IT department, whose help was key to acquire the Power BI licences.

1.1. Report Restructuring Goals

Considering the dissertation is relying on a report restructuring, it does not answer an actual research question. The main purpose is to improve data pre-processing, data visualisation and data analysis by developing an R Script and a dashboard from scratch in Power BI. Therefore, the main goal is to improve KPI monitoring with business intelligence tools and in order to achieve that goal, there are some objectives that need to be followed:

- Improve data pre-processing through R Studio
- Formalize steps in R Script
- Remove unnecessary data
- Creation of a dashboard with Power BI
- Improve data visualisation and data analysis through Power BI
- Create measures

There are high incentives for the improvement of the data pre-processing and the construction of this dashboard since TNC is one of the cores KPIs once it measures the conversion of opportunities. The report is important considering that is a significant KPI that is particularly hard and time-consuming to analyse and, can be affected by many variables. The report was previously done using four databases in different excel files that needed to go through many steps individually to prepare for later bind the four of them and create the main database. By following the process of preparing the database for the analysis and understanding the reasons for each step, was possible to conclude that the process could be simplified and partly automatised.

The analysis was done based on the database prevenient from the four excel files and many pivot tables measuring the conversion in general and with more detail concerning, for example, the type of client and type of channel.

Considering the report did not have any visual representation of the KPI besides the pivot tables, the creation of the dashboard will allow a smoother analysis, easier development of first insights and faster decision-making.

1.2. Research Methodology

The report restructuring, being the practical element of the dissertation, will follow the Action-Research methodology. Action-Research is about gaining feedback from experiments in real situations with practitioners, modifies the theory according to the results of the experiment and try again. Because Action-Research has a more practical component, when analysing the results of some changes emerge new ideas for improvement.

The report restructuring, being the practical element of the dissertation, will follow the Action-Research methodology. Because Action-Research has a more practical component, when analysing the results of some changes emerge new ideas for improvement.

The action-research methodology is based on cycles in which each one of them there is a diagnosing stage, action-planning stage, action-taking stage, evaluating stage, and specifying learning stage. Therefore, for the restructuring of the report, there will be two sections, one for each cycle, called Data Pre-Processing and Data Visualisation as each of them are the main areas with more room for improvements. As expected, many turns were made in each cycle with the goal of constant improvement and meaning that even when finally moving to the next cycle it does not mean it will not be needed to go back again and reformulate the plan since the next cycle is always dependent of the previous one.

1.3. Dissertation Structure

This dissertation is composed by five chapters. The current chapter, Chapter 1, describes the background in which the study was performed and the reasons and needs for the emerging of the restructuring itself. It also describes the main goal of this dissertation, the methodology used and structure of the dissertation.

The second chapter provides a theoretical framework about the concepts that will be addressed for the development of the project such as Decision-making, KPIs, Big Data and Business Intelligence tools.

The third chapter gives a slight context on the reason for the internship and why the KPI analysis needs improvements and goes more deeply into explaining the goals. It also provides a theoretical description of the methodology used.

The fourth chapter presents how the analysis of the KPI was firstly performed and the main problems along it. Followed by the changes made to the KPI report and ends by presenting the comparison between the first base report and the one with the actual changes in order to highlight and prove the progresses made.

Lastly, the fifth chapter, point out the goals achieved, sums up all the conclusions taken from all the work carried out, the main contributions of the study, both to controllers and end-users, and recommends further studies or improvements that can be done.

Second Chapter

2. Literature Review: Business Intelligence to Monitor Key Performance Indicators in Operations Management

The current chapter is divided in three subchapters that represents the principal concepts for this dissertation. The first subchapter is about Key Performance Indicators and Decision-Making, Big Data in Decision-Making, and Business Intelligence, which includes more focused information on business intelligence tools and, more specifically, Power BI.

The goal of this structure is to relate decision-making in operations management with KPIs and then, consequently, the role of big data in decision making and how business intelligence tools can enhance decision-making.

2.1. Key Performance Indicators and Decision-Making

Operations Management (OM) is responsible for managing the resources and processes required by any organisation to produce goods or intangible services (Barnes, 2018). It is often referred to as the discipline that uses scientifically based analytical methods to make optimal decisions for an organisation (Choi et al., 2018)

Kumar (2022) believes there are three levels of significance for decision-making in OM, which are strategic decisions, tactical decisions, and operational decisions. Strategic decisions are regarding long-term goals, philosophies, and values, and are the riskiest and most uncertain ones considering their reach into the far future. Tactical decisions support the strategic ones, being medium-term goals with a medium range and significance. While strategy comprehends the future vision of a business, tactics involve the practical and actual steps needed to accomplish that vision. Operational decisions are everyday decisions that support tactical decisions, with direct impact and of short term and range.

To quantify the efficiency and effectiveness of operations management, a range of detailed indicators are set to carry out the strategic goals of process management and improvement, which are called Key Performance Indicators (KPIs). KPIs reflect the company's critical success factor through quantifiable and strategic measurements.

KPIs are crucial for decision-making in an enterprise. However, the approach to analysis and composition used to formulate KPIs can lead to errors. If an analysis relies only on averages, it may not allow discriminating between variations, which are common in processes. It is possible to identify this differentiation by using control charts. Nonetheless, when multiple charts covering different units and measurement scales are presented, systemic interpretation can be hindered (Peloia et al., 2022).

A systematic method of analysis of KPIs it is to simultaneously monitor the KPIs connected to distinct aspects interconnected in a complex process to get a universal sight and prioritise the balance between them (Kijima & Jones, 2018).

Regarding the characteristics of indicators, Arango Serna et al. (2017) believes that when designing an indicator, it is necessary to consider some characteristics and those characteristics should follow the SMART criteria. This means the indicator should be Specific, Measurable, Achievable, Realistic and Time-Based. When designing an indicator, to be specific, for effective planning, the goals should be explicit and precise about what, where and when. The indicator needs to be measurable in a way it should define what evidence will prove and quantify the progress and benefits. Realistic, which means being rational and understanding if it is something possible to achieve or not. Finally, the indicator also needs to be Time-based, which means setting a realistic, yet, the ambitious deadline for task prioritisation and encouragement.

Key Performance Indicators Categorization

Kang et al. (2016) developed a hierarchical structure of KPIs, where it's considered imperative to group KPIs by various categories and levels, defining clear cross-links. The structure developed by Kang et al. (2016) is illustrated in figure 1, consisting of three categorised levels: direct measurement or supporting elements, basic KPIs and comprehensive KPIs. Moreover, the authors also grouped parameters according to their functions and attributes.

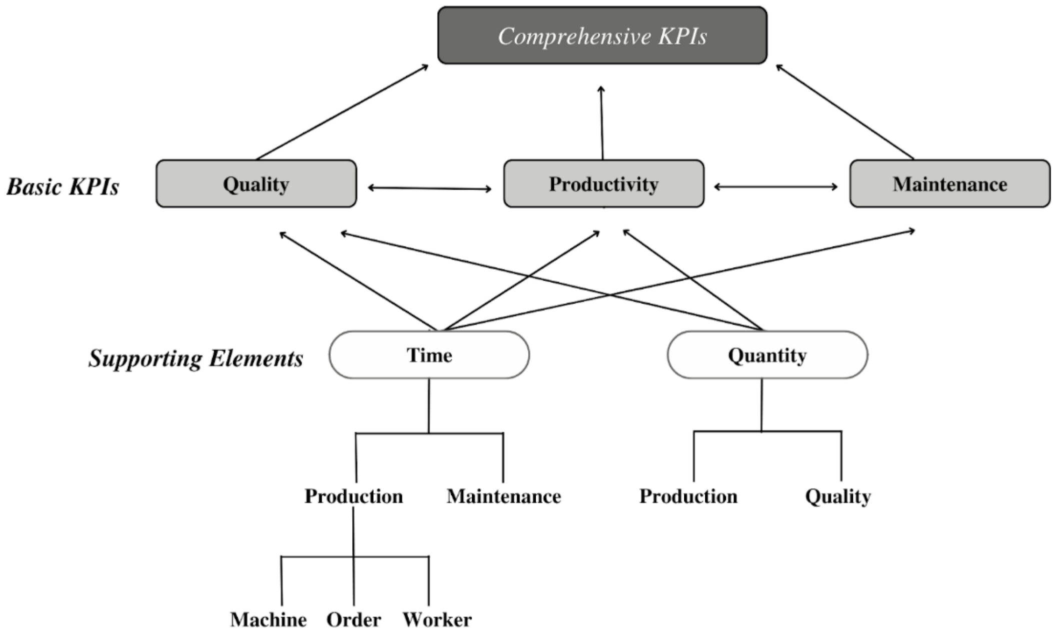

Figure 1: Hierarchical Structure of KPIs by Kang et al. (2016)
Source: International Journal of Production Research

Moktadir et al. (2020) also considered that KPIs can be combined with a group of elements with similar characteristics. Therefore, KPIs need to be rationally categorised to explore the significant interactions between them. Thus, it is indicated to arrange KPIs into many groups at different levels with specific cross-links between them. Considering experts' suggestions, Moktadir et al. (2020) believe that KPIs can be gathered under six categories: management, operations, quality, economic, social, and environmental.

2.2. Big Data in Decision-Making

Nowadays, it is possible to gather a large set of necessary data and estimates, supporting the acquisition and calculation of KPIs due to the modern tools provided by information technologies. (Zhu et al., 2017)

Organisations that can exploit internal and external generated data, can transform their operational capabilities. By providing decision-makers with larger volumes of legitimate and opportune information, or automating decision-making processes, it is believed that Big Data can benefit organisations, individuals, and society. (Bughin et al. 2011, Barton and Court 2012, as cited in Matthias et al., 2017).

Big data analytics enable companies to use data as a strategic asset for decision-making, at three levels (Dehbi et al., 2022). The large amounts of data, generated by Industry 4.0's technologies, can be processed to use in decision-making to create value for companies. That value is created through data analysis and integration into strategic and operational activities (Bordeleau et al., 2018). Industry 4.0 is defined by Ivanov et al. (2021, pp.3) "as the integrity of technologies, organisational concepts and management principles underlying a cost-efficient, responsive, resilient, and sustainable network, data-driven and dynamically and structurally adaptable to changes in the demand and supply environment through rapid rearrangement and reallocation of its components and capabilities". According to Statista (2022), nowadays, with modern technology, it is possible to deliver massive structured and unstructured data sets in almost real-time. Big data analytics empower companies to develop strong insights and increase competitive advantage. It is expected that, by 2029, the big data analytics market will reach 655 billion U.S. dollars (Statista, 2022).

Big Data Frameworks

There are several Big Data frameworks to treat and analyse data, suggested by many authors such as H Zadeh et al. (2021), Özemre & Kabadurmus (2020), and Ankam (2016). These authors suggested a framework based on big data analytics methodology, on the Cross Industry Standard Process for Data Mining (CRISP-DM) and a Big Data project life cycle, respectively. This dissertation will be focusing on the CRISP-DM approach since it is the one more frequently used.

H Zadeh et al. (2021) suggested a framework based on big data analytics methodology to demonstrate the steps to be followed for analytics to illustrate the phases of social media analytics. The six steps that need to be followed are data collection, data storage, data pre-processing, data integration, data modelling and data visualisation.

Özemre & Kabadurmus (2020) suggest a slightly different approach, based on the CRISP-DM (Cross Industry Standard Process for Data Mining). The steps of CRISP-DM are business understanding, data understanding, data preparation, modelling, and evaluation. According to Schröer et al. (2021), Business Understanding is about evaluating the business situation to get an overall vision of the available and required resources. It is also in this step that the most important question is answered: "What is the data mining goal?" There are many types of data mining and, therefore, the chosen one should be justified, as well as the data mining success criteria (Schröer et al., 2021). It is imperative to create a project plan. The second step, Data Understanding, includes many crucial tasks such as collecting data from the various data sources, exploring, and describing it and always verifying its quality (Schröer et al., 2021). When describing the data, it should be done by using statistical analysis and determining characteristics and their relations (Schröer et al., 2021). The third step, Data Preparation, consists in defining inclusion and exclusion criteria when selecting data (Schröer et al., 2021). If data does not have good quality, it is necessary to clean it (Schröer et al., 2021). Although the construction of attributes might vary depending on the chosen model on the step of Business Understanding (Schröer et al., 2021). Many different methods for the various steps are possible and it all depends on the model chosen previously (Schröer et al., 2021). After data preparation follows the Data Modelling step, which is about choosing the modelling technique, and developing the test case and the model (Schröer et al., 2021). Even though all data mining techniques can be applied, the choice will, once again, depend on the business problem and the data that is going to be used (Schröer et al., 2021). Yet, the truly significant part is how to explain the chosen data mining technique (Schröer et al., 2021). Certain criteria must be defined to build the model. To appraise the model, it is convenient to evaluate it against evaluation criteria and select the greatest ones (Schröer et al., 2021). Following Modelling is Evaluation, which is the step to check the results against the previously defined business objectives (Schröer et al., 2021). Thus, those results need to be interpreted and, consequently, actions need to be established (Schröer et al., 2021). After, the general process should be reviewed. Finally, the last step is Deployment, which is often described in the user guide (Schröer et al., 2021). It can be a final report or a software component, where it is described the planning of the deployment, monitoring and maintenance (Schröer et al., 2021).

Big Data Project Life Cycle

Ankam (2016) suggests there is a Big Data project life cycle that encompasses the following phases: Identifying the problem and outcomes, identifying the necessary data, data collection, pre-processing data, performing analytics, and visualising data. The project life cycle phases are described in figure 2.

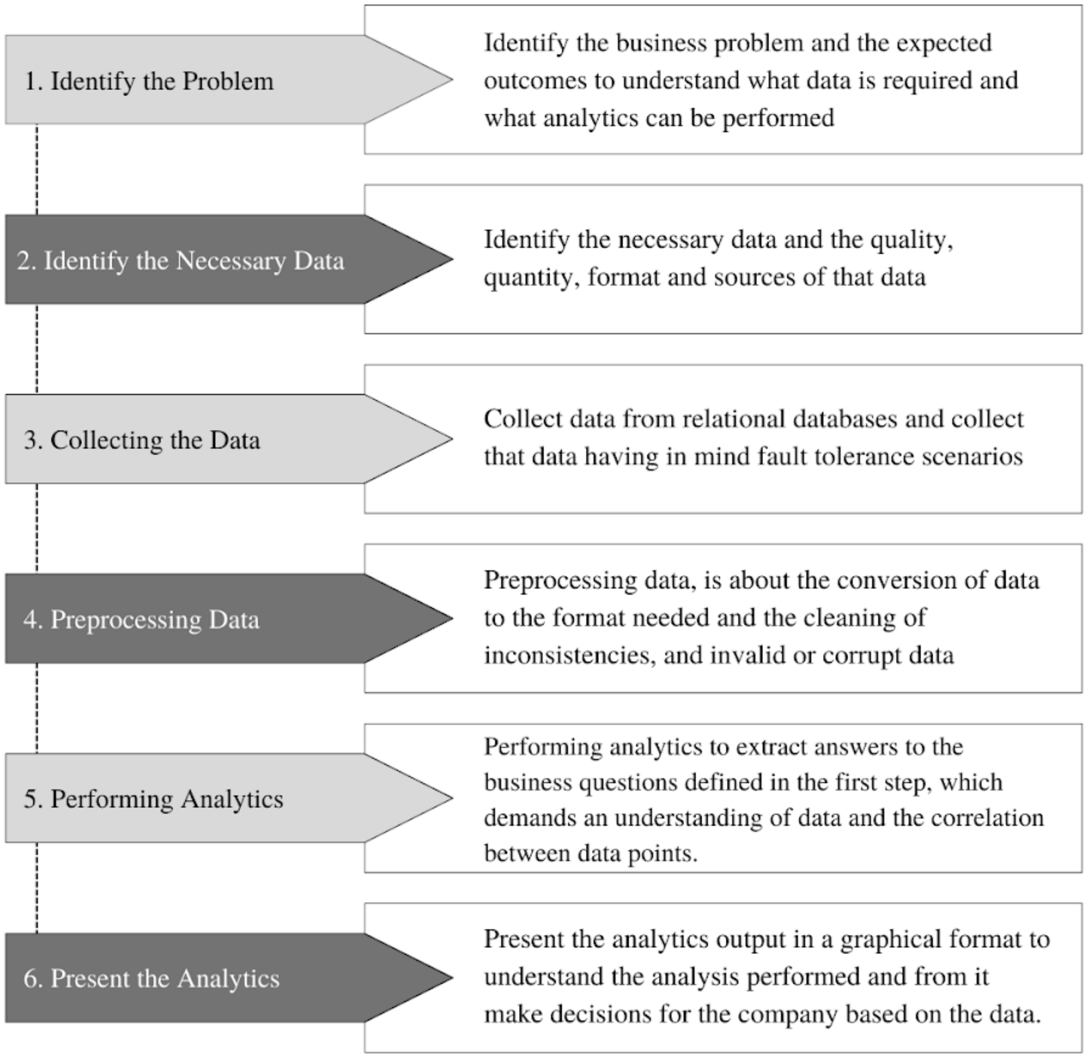

Figure 2: Big Data Project Life Cycle

Source: Ankam (2016)

2.3. Business Intelligence

Business Intelligence (BI) can be defined in various ways. Negash & Gray (2008, as cited in Larson & Chang, 2016) defines Business Intelligence as a "data-driven process that combines data storage and gathering with knowledge management to provide input into the business decision-making process. BI enables organisations to enhance the decision-making process and requires processes, skills, technology, and data." (p.2). Gatner (2013) and Halper (2015), as cited in Larson & Chang (2016), broadened Business Intelligence to an umbrella term that comprehends applications, tools, infrastructure, and practices that provide access and analysis of information to enhance performance and decision-making.

Business Intelligence tools function as an instrument for organisations to monitor data and create business insights that are essential components to deliver results driven by smarter and optimal decisions. (Nagar et al., 2016). There are many types of Business Intelligence tools ranging from analytics and big data statistics to reporting tools and dashboards that instantly provide information across indicators (Nagar et al., 2016).

Richardson et al. (2020) characterises business intelligence platforms as a full analytical workflow supported by their user-friendly functionality, starting with data preparation to visual exploration and insights generation. Data visualisation features on Business Intelligence platforms are not as differentiative as they used to be. Instead, the differentiation leans more on integrated support for enterprise reporting capabilities and augmented analytics (Richardson et al., 2020).

Richardson et al. (2020) consider that Business Intelligence platforms standards include 15 crucial capability areas which are security, manageability, cloud, data source connectivity, data preparation, model complexity, catalogue, automated insights, advanced analytics, data visualisation, natural language query, data storytelling, embedded analytics, natural language generation and reporting. Considering the 15 areas mentioned, the authors segmented the various platforms in a matrix, named Magic Quadrant, according to their ability to execute and completeness of vision, as illustrated in figure 3.

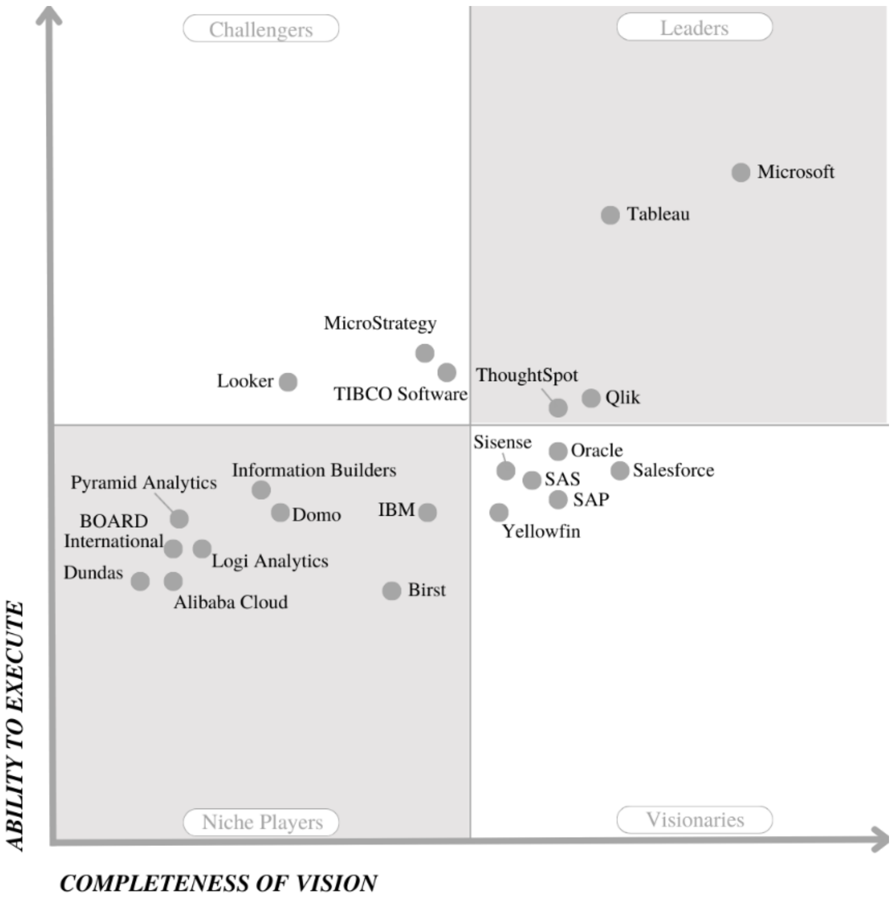

Figure 3: BI Platform Magic Quadrant by Richardson et al. (2020)

Source: Richardson et al. (2020)

Considering a Gounder et al. (2016, as cited in Tavera Romera et al., 2021) survey, a comparison is made between some of the tools that are more suitable for data visualisation was also mentioned by Richardson et al. (2020) such as Tableau, Cognos, Sisense, SAP Business Objects, Microsoft Power BI, Domo and Dundas and their applications specialisations, as shown in table 1.

BI Tool	Applications	Strengths
Tableau	Data visualisation products	Ease of visual exploration and data manipulation
Cognos	Performance management products	Includes enterprise reporting, governed and self-service visual exploration, and augmented analytics in just one platform.
Sisense	Analyses and visualises big data sets and ideal tool for building interactive dashboards	Support for complex data mashups. e.g., Automatically deduplicate incorrect or misaligned data and group similar strings
SAP Business Objects	Real-time Business Intelligence	Continually developing augmented capabilities by adding support for automated time-series analysis and explainable findings.
Microsoft Power BI	Interactive visualisations with self-service business intelligence capabilities	Innovative capabilities for augmented analytics and automated machine learning.
Domo	SaaS	Rapid deployment is enabled by its fast connection to enterprise applications.
Dundas BI	Data visualisation	Users can create flawless reporting content in the same environment that is used for the drag-and-drop dashboard and self-service design.

Table 1: BI Tools Applications and Strengths

Source: Adapted from Gounder et al. (2016, as cited in Tavera Romera et al., 2021)

According to the Magic Quadrant of Richardson et al. (2020), among the tools mentioned before, Power BI is considered a Leader regarding its complete and visionary product roadmap and extensive market reach. This tool also allows the preparation of data, visual data discovery, interactive dashboards, and augmented analytics.

2.3.1. Power BI

Microsoft Power BI is a suite of Business Intelligence and analytical tools with an extensive range of data sources that can be used to analyse data, report, and share insights. It differentiates itself by its user-friendly dashboards with interactive data visualization, and simple features, available on every device such as applications, desktops, and mobiles (Bhargava, 2018; Gowthami & Kumar, 2017).

Power BI includes Power Query, Power Pivot, Power View, Power Map, Power Q&A and Power BI Desktop (Gowthami & Kumar, 2017). Power Query is a self-service ETL tool (Extract, Transform, and Load) tool, runs an excel add-in, which allows one to accept data from multiple different sources and manipulate it into a form and load it into Excel (Gowthami & Kumar, 2017). Power Pivot is an in-memory data modelling component that provides extremely fast incorporation, calculation and strongly compressed data storage (Gowthami & Kumar, 2017). Power View is an interactive visualisation tool that provides a user-friendly drag-and-drop interface in order to create fast and effortless visualisations of the data in Excel Workbooks (Gowthami & Kumar, 2017). Power Map is a three-dimensional data visualisation tool that allows one to look at information from new and different perspectives that usually cannot be seen in traditional visualisations such as tables and charts (Gowthami & Kumar, 2017). Power Q&A identify the words entered and find the answer. Finally, Power BI Desktop is a drag-and-drop analytical tool that allows one to place visuals on a flexible and fluid canvas (Gowthami & Kumar, 2017). Power BI has many features such as Dashboards, Visualisations, Connectors for SaaS services, Live-Connectivity to SaaS services and Power BI Designer. Dashboards are used to arrange various data visualisations in a single interface and easily monitor KPIs. (Gowthami & Kumar, 2017)

2.3.1.1. Power BI Dashboards

A dashboard is a "visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen" (Bach et al., 2022).

Bach et al. (2022) define some rules to construct a dashboard such as, not overwhelming users, avoiding visual clutter and poor visual design, carefully choosing KPIs, aligning with existing workflows and not showing too much data. A dashboard should also have functional and visual features, provide consistency, and interaction affordances and manage complexity (Bach et al., 2022). Visually, the dashboard should have symmetrically organized charts, charts grouped by attribute, clearly separated, and ordered according to time (Bach et al., 2022).

According to SAP Press, there are 10 rules for dashboard design. The first five rules regard the choice of appropriate visualisation types and the next five regard the optimization of the dashboard for decision-making, which are detailed in table 2.

Ensure Appropriate Visualisations	1. Use containers that are best suited to showing and reading your type of data.
	2. Compare data using charts appropriate for the type of comparison. Use truthful scale factors.
	3. Show data and its relation as part of a whole.
	4. Bind the data to where it makes sense geographically.
	5. Use charts that plot the relationship between measures, and the distribution of values within a measure.
Ensure Dashboard Optimization	6. Build using a grid to align and scale elements consistently.
	7. Understand colour theory to use colour appropriately.
	8. Contrast a single neutral colour for graphic elements with visible colours that have known semantic meaning for data highlights and alerts.
	9. Keep the dashboard design uniform and coherent with the corporate style and visual standards.
	10. Ensure everything in the dashboard is relevant and revealing so the user understands the data and is empowered to make a confident decision.

Table 2: SAP 10 Rules for Dashboard Design

Source: SAP Press

However, from a Sisense (2023) point of view, there are only four key principles to designing a dashboard, which is Making the complex simple, telling a clear story, expressing the meaning of data, and revealing details as needed. Nevertheless, Sisense also mentions four rules to detect poor design choices immediately, which are the five-second rule, the inverted pyramid for logical layout, minimalism: less is more, and choosing the right data visualisation, described in table 3.

The Five-Second Rule	A dashboard should answer the most frequently asked business questions in 5 seconds, without the need of scanning through it for several minutes to answer them.
The Inverted Pyramid	Display the most significant insights on the top part of the dashboard, trends in the middle, and granular details in the bottom
Less is More	Each dashboard should contain no more than 5-9 visualisations
Choosing the Right Data Visualization	Select the appropriate type of data visualisation according to its purpose. Always consider which type of information is trying to be delivered. It can be a relationship between two variables, a comparison between two or more variables, a composition breaking the data into separate components or a distribution of values within data.

Table 3: Four Rules to Detect Poor Dashboard Design

Source: Sisense

Third Chapter

3. Methodology

After the theoretical framework provided by the previous chapter considering the many relevant concepts related to the project on which this dissertation is based on, the current chapter will provide the methodology adopted throughout the report restructuring.

The current chapter, chapter three, is divided in three sections: introduction to the project goals in subchapter 3.1, research contextualization for the development of the project in subchapter 3.2 and, lastly, a theoretical description in subchapter 3.3.

3.1. Project Goals

As previously mentioned, the goal of this dissertation is to use Business Intelligence in order to monitor KPIs in operations management, with data pre-processing tools to speed up the process and visualisation tools, for faster decision-making and better understanding of the variables that affect the KPI, *Total Net Conversion* (TNC).

Since this dissertation is being developed as an internship report, it does not have a concrete research question based on literature gaps. Considering that, to achieve the main goal, easier and faster decision-making, the purpose of the research is to fulfil the following objectives:

1. Improve data pre-processing through R Studio by running all the steps and calculations previously done in excel

2. Creation of a dashboard with all the variables that explain and affect the KPI
3. Implementing measures
4. Improve data visualisation

The internship occurred in Carglass, which will be introduced in chapter 3.2. Even though the KPI in question is about measuring conversion, there are many supporting elements, as mentioned in the previous chapter by Kang et al. (2016), that can affect the performance of this KPI and are part of it. Because of the complexity of the KPI, to analyse it was primarily needed four databases, extracted with queries, and then compiled in an excel file and complemented with other information, which was very time-consuming, did not leave much time to analyse the information and take actions.

Considering that, the theme proposed by Carglass was "Improving KPI monitoring" since the company needed a faster and easier way to analyse the information and spot potential red flags at first sight. The KPI considered is, as mentioned above, TNC which has the goal of measuring the conversion of the total opportunities arriving to jobs as well as what is influencing the conversion in the periods in analysis.

However, besides the visual guidance need, when analysing the process and the problem, was also spotted the need of doing data pre-processing since it was done with four different heavy excel files that needed to be compiled together but with a very rigorous and time-consuming method, with many steps and rules that needed to be followed always in the same order with no exceptions and could still lead to some technical errors.

3.2. Research Contextualization – Carglass

"Making a difference with real care" - Belron.

Carglass is a company that is part of the Belron Group, which is the world's leader in glass repair, replacement, and recalibration (Belron, 2023). Belron operates in 40 different countries and counts with more than 28.000 employees, who serve almost 15 million customers per year (Belron, 2023). Besides Carglass, Belron owns brands such as Safelite, Autoglass, Lebeau, O'Brien, Apple Auto Glass, Smith & Smith, Duro, Laddaw, Origlass, Hurtigruta Carglass, Autoglass Specials, Speedy Glass, Vanfax and Laser (Belron, 2023).

Carglass started operating in Portugal in 1989, with agencies primarily located in Porto and Lisbon. (Carglass, 2023) In 2017, Carglass acquired the biggest franchise of ExpressGlass as the first step of the company's plan of expansion in Portugal. This step allowed Carglass to include ten more agencies, becoming 60 agencies in total. From this action, it also resulted in an increase of 10% of the number of employees. (infofranchising, 2017) In 2023, Carglass Portugal has 67 agencies spread all over the country with Açores and Madeira included and 30 vehicles that provide mobile service in order to guarantee total assistance wherever the customers are (Carglass, 2023).

The company was the first to arrive in Portugal and is a pioneer in calibrating vehicles with Advanced Driver Assistance Systems (ADAS) technology, having invested in the development of their employees and certifying their technicians by the Institute of Motor Industry (IMI) (Carglass, 2023). Besides that, Belron Group which Carglass is part of, also invests in technology to improve the daily work-related activities of its employees, having developed by its technical research and development team the Belron Way of Fitting which is a guide with the 40 steps needed to know by technicians in order to guarantee quality and safety when performing the services (Belron, 2023). Also keeping in mind, the safety of its employees, the 1-Tek was exclusively invented, developed, manufactured, and launched for Belron, whose utility is to help a single technician lifting large windscreens that usually would be carried-out by two people (Belron, 2023). The Ezi-Wire is also exclusive to Belron and was developed once again to reassure the safety of its employees and ergonomic by instead removing the windscreen with cut-out knives that could damage the vehicles, removing it effectively with a mechanical wire (Belron, 2023). Belron Group also developed the Technical Master Database which is an online database only available for Belron technicians and, therefore, Carglass technicians and allows them to correctly identify the products needed for each vehicle across the globe (Belron, 2023).

3.3. Method

In order to achieve the restructuring goals proposed in subchapter 3.1, the methodology chosen was Action Research. This choice had into consideration the goal of the methodology approach which is creating knowledge about action through action. According to Avison et al. (1999), in action research gains feedback from experiments in real situations with practitioners, modifies the theory according to the results of the experiment and tries again. Action research is also defined by Reason (1997) as having a double goal which is to create knowledge and action directly useful to a group of individuals through research (...), and empowering people at a second and deeper level through the process of constructing and using their own knowledge.

However, the term "action research" was first used by Kurt Lewin in 1946 to describe "*a spiral action of research aimed at problem solving*". (Walker, 1993)

There are four different types of action research which are action research focusing on change and reflection, action science which tries to solve disagreements between espoused and applied theories, participatory action research which emphasises the participants collaborations and lastly, action learning for programmed instruction and experiential learning (Avison et al., 1999). For this dissertation will be used action learning. Nevertheless, according to Susman & Evered (1978 as cited in Avison et al., 1999) to attain scientific exactitude, it is commonly enforced an additional structure to action research projects. There is a cyclical process composed of five stages which are diagnosing, action-planning, action-taking, evaluating, and specifying learning. The diagnosing stage is expected to identify primary problems for further analysis. In the action planning phase, it is expected to develop a set of organisational actions and how to operationalize them in order to relieve or improve the primary problems identified in the diagnosis. The third step, action taking, is where is supposed to execute the actions defined before and produce additional information with the observations and outcomes of the action. With the observations of the outcomes of the action, follows the evaluation stage where the goal is to understand the impacts of the outputs of the action on the problems and, finally, specify the learning. If the action's outcomes are unsatisfactory, the revised narrative line serves as the basis for a new diagnosis stage, which triggers another iteration of the action research cycle. The ending point of the action research cycles in when the issue is solved or the learning stages stop producing relevant changes. Wadsworth (1998, as cited in Walker, 1993) agrees that instead of a standard linear model, action research is cyclic in which steps are also multiple iterations of planning, acting, observing, and reflecting.

In chapter four, the report restructuring will consider the action research method defined by Avison et al. (1999) illustrated in figure 4.

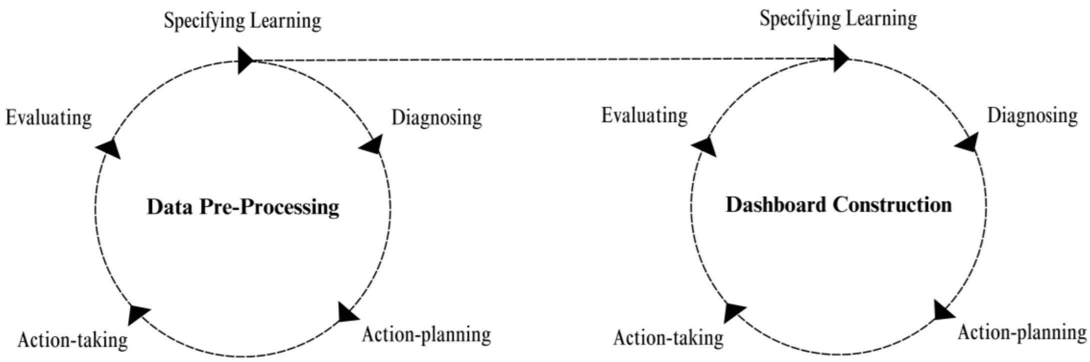

Figure 4: Action Research: Adapted Model

The data pre-processing cycle will comprehend the research perspective in business data analytics by Ekka & Jayapandian (2020) which comprehends five steps in R programming, which are:

1. Tidy: which consists in making sure the structure of the data frame is consistent with the columns named and arranged properly and white spaces taken into account.

2. Transform: which is about extracting and using only the necessary data but also creating missing and needed variables and functions.

3. Visualise: which consists in seeing if the data set provides a consistent result for the problem, after the data transformation.

4. Programming: the step where the variables created previously are put into appropriate functions and the results set is compared to the desired output.

5. Communication: Finally, the final result must be clear and understandable.

Finally, the development of the dashboard will be considering the 10 rules for dashboard design of SAP Press and the structure will have into account the three levels of significance for decision-making in OM by Kumar (2022), which are strategic, tactical, and operational mentioned in the previous chapter.

Fourth Chapter

4. Report Restructuring

After the theoretical framework of the methodology chosen for the report restructuring in the third chapter, the current chapter consists in describing in detail the practical application that Action Research methodology provided. The next three subchapters correspond to the three fundamental stages of the restructuring. In that way, subchapter 4.1 will focus on analysing what was done in the base report and its performance, in terms of pre-processing and data analysis, and identifying aspects that could be improved. In subchapter 4.2 is explained what changes were made, the reasons for those changes and how they were reached. Finally, subchapter 4.3 presents the final report, comparing it to the base report and showing the evidences of improvement.

The subchapters will address the two cycles of Action Research, Data Pre-Processing, and Data Visualisation, since it is where was identified the opportunities of improvement. It must be emphasised that both cycles went through several turns.

4.1. Base Report

Currently, Carglass has a hard time measuring one of its KPIs, which was already mentioned in subchapter 3.1, TNC. In order to create the necessary database to analyse this KPI, it is necessary to export four reports with queries from SQL to Excel files and compile the output of the four of them after very precise and methodical steps that can easily lead to errors. The database called "*Dados FS*" has all the jobs performed since the beginning of the year, being the main database used to compile the other three databases. Besides "*Dados FS,*" there are two databases in which one includes the opportunities yet to be identified from the branches and the opportunities yet to be identified from the *Customer Contact Centre* (CCC). The fourth database is the one that has the details of the various typification codes of the channels with the respective car plate number, when they come from the CCC. All these databases have two common variables which are the unique ID of the work order, named *NUMERO ORDEN,* and the car plate number, named *MATRICULA* which is the one used in order to track information. A first analysis was done to the process of developing this database and the need and reasons for each step. The four databases extracted with queries besides having common variables, the order of the columns in the output varied within all of them, which was also time-consuming when managing the data in Excel.

Before compiling the four databases it is necessary to tide individually each of them which involves removing duplicates, order data according to its earliest and latest entries, correct inconsistencies and removing unnecessary data.

Being "*Dados FS*" the main database it is where the first steps are made. Because the database come with some flaws, such as having many different date columns but all with different date formats or not even in a date format, the first step is transforming the date columns to the same date type for consistency. The second database worked is "*Orçamentos Agência*". Because the opportunities identified in "*Dados FS*" come from the same channel as "*Orçamentos Agência*", it is necessary to identify the opportunities that exist simultaneously in "*Dados FS*" and "*Orçamentos Agência*", and remove the common records in "*Orçamentos Agência*" since the records in "*Dados FS*" are the opportunities already converted and what is in "*Orçamentos Agência*" are, therefore, considered duplicates. Those common opportunities are identified by the unique ID variable, the car plate number.

The third database worked is “*Orçamentos CCC*”. The goal with this step is exactly the same as in the previous database, tracking the records that already exist in “*Dados FS*”, considering again that the ones in “*Dados FS*” are opportunities already identified and/or converted. However, the opportunities in “*Orçamentos CCC*” come from a different channel than “*Dados FS*”, and because of that, instead of removing the records in “*Orçamentos CCC*” that exist simultaneously in the two databases, the common records are kept in both databases for tracking information and analysis purposes. Yet, when the opportunities in “*Orçamentos CCC*” that also exist in “*Dados FS*”, the status has to be changed and is declared as annulated with the respective annulation code as “duplicated”.

In the database “*Operador*” are all the codes for the channel specifications and, in this database, is where is done the match between that code and the respective description. After, the same database in ordered from the earliest entry to the latest in order to find the first entry of each unique ID, *MATRICULA*. However, because some of the car plate’s numbers are false such as 00-00-00, instead of looking for the first entry of the car plate, the search is done with the work order number, which is the second unique ID variable.

Finally, the channel descriptions from “*Operador*” are matched accordingly to its car plate number in “*Dados FS*”.

In table 4 is provided a short description of the information provided by each database.

Databases	Information provided
Dados FS	Main database with all the work orders created since the beginning of the year and its most recent status which can be confirmed, pending or annulated.
Orçamentos Agência	Opportunities not identified that came through the branch channel
Orçamentos CCC	Opportunities not identified that came through the CCC channel
Operador	Workorders and respective channel specifications codes

Table 4: Databases and respective information provided

After removing all the unnecessary information and tiding each database, it is when "*Orçamentos Agência*" and "*Orçamentos CCC*" are compiled with "*Dados FS*", having finally the database ready to perform the analysis.

The analysis consists in analysing the conversion, in general and then with more specification such as per region, per type of client, per channel and so on. The analysis is done by already built pivot tables with different purposes and variables but no visual representation such as analysis of tendencies and performance overtime.

4.2. Improvements

Considering all the steps mentioned in the previous subchapter concerning all the data preparation, an R Script was developed in order to automatise the process and improve efficiency. After finalizing the R Script, a dashboard was created in order to improve data visualisation and data analysis, considering there was no visual representation of the KPI.

4.2.1. R Script: Data Pre-Processing

With the goal of automatising the process and making it less time-consuming and prone to error, an R Script was developed to assure that all the rules were respected and all the steps were done with the right order. In the R Script, each database is treated first individually, starting always with the first step which was tidying each of them. In the first database the tidying needed was to assure that all the columns in common had the same names in order to smoothly bind the databases together later. In table 5, it is a summary of the databases that required that step.

	TIDY	
Databases	Rename Columns	Rearrange Columns
Dados FS	X	X
Orçamentos Agência	X	X
Orçamentos CCC	X	X
Operador	X	X

Table 5: Tidying steps required by each database

The next step was transforming the databases, again each of them individually. Transforming the data involves extracting and using only the necessary data but also creating missing and needed variables and functions, as mentioned in subchapter 3.3. Considering that, only "*Dados FS*" did not suffer any alteration at this stage. However, as marked in table 6 and as mentioned in subchapter 4.1 in "*Orçamentos Agência*" is removed the duplicates, but in R, with a subset function, as shown in figure 5. Three empty columns were added in order to bind the database smoothly with "*Dados FS*".

	TRANSFORM		
Databases	Remove Columns	Remove unnecessary data	Add new variables
Dados FS			X
Orçamentos Agência		X	X
Orçamentos CCC	X	X	X
Operador			X

Table 6: Transformation steps required by each database

```
data_TNC_Orc_AG$DUPLICATE <- data_TNC_Orc_AG$MATRICULA %in% c(data_TNC$MATRICULA)
table(data_TNC_Orc_AG$DUPLICATE)
data_TNC_Orc_AG<-subset(data_TNC_Orc_AG, DUPLICATE != "TRUE"|is.na(data_TNC_Orc_AG$MATRICULA))
data_TNC_Orc_AG$DUPLICATE <- NULL
```

Figure 5: Removing Duplicates in "*Orçamentos Agência*" in R

In “*Orçamentos CCC*” is also necessary to remove a column that does not bring any value for the analysis and remove the records that are not considered opportunities when analysis conversion.

As mentioned in the previous subchapter, in “*Orçamentos CCC*” the next step was to, instead of removing the duplicates, filtering the ones that already exist in “*Orçamentos Agência*” and change the status in “*Orçamentos CCC*” as annulated which is represented with the letter “A” in figure 6 and use the respective “duplicated” code. The same procedure is repeated but between “*Orçamentos CCC*” and “*Dados FS*”, as illustrated in figure 6.

```
data_TNC_Orc_CCC$DUPLICATE <- data_TNC_Orc_CCC$MATRICULA %in% c(data_TNC_Orc_AG$MATRICULA)
table(data_TNC_Orc_CCC$DUPLICATE)
table(data_TNC_Orc_CCC$ESTADO)
table(data_TNC_Orc_CCC$CODIGORAZONANULACION)
data_TNC_Orc_CCC$ESTADO <-ifelse(data_TNC_Orc_CCC$DUPLICATE == "TRUE" , "A", data_TNC_Orc_CCC$ESTADO)
data_TNC_Orc_CCC$CODIGORAZONANULACION <-ifelse(data_TNC_Orc_CCC$DUPLICATE == "TRUE", "1027", data_TNC_Orc_CCC$CODIGORAZONANULACION)
data_TNC_Orc_CCC$DUPLICATE <- NULL
data_TNC_Orc_CCC$DUPLICATE <- data_TNC_Orc_CCC$MATRICULA %in% c(data_TNC$MATRICULA)
table(data_TNC_Orc_CCC$DUPLICATE)
table(data_TNC_Orc_CCC$ESTADO)
table(data_TNC_Orc_CCC$CODIGORAZONANULACION)
data_TNC_Orc_CCC$ESTADO <-ifelse(data_TNC_Orc_CCC$DUPLICATE == "TRUE" , "A", data_TNC_Orc_CCC$ESTADO)
data_TNC_Orc_CCC$CODIGORAZONANULACION <-ifelse(data_TNC_Orc_CCC$DUPLICATE == "TRUE", "1027", data_TNC_Orc_CCC$CODIGORAZONANULACION)
sum(is.na(data_TNC_Orc_CCC$CODIGORAZONANULACION))
data_TNC_Orc_CCC$DUPLICATE <- NULL
```

Figure 6: Finding and Manipulating Duplicates in "*Orçamentos CCC*"

In both “*Orçamentos CCC*” and “*Orçamentos Agência*”, three new empty columns are created in order to later bind the three databases smoothly.

In “*Operador*”, the database is ordered from the earliest entry to the latest entry and unnecessary data is removed by a subset function, as illustrated in figure 7.

It is added a new column in order to match the description of the channel with the respective typification code by merging the “*Operador*” database with the list of the channels’ descriptions, also illustrated in figure 8.

```
data_TNC_Operador<-subset(data_TNC_Operador, Origem != "STOCKM")

data_TNC_Operador <- merge(data_TNC_Operador, equi_canal, by = "Origem Chamada", sort = F, all.x = T)
```

Figure 7: Removing unnecessary data from "*Operador*"

Finally, the three databases are bind together vertically and ordered again from the earliest to the latest entry.

```
data_TNC <- rbind(data_TNC,data_TNC_Orc_AG, data_TNC_Orc_CCC)

data_TNC <-data_TNC[order(as.Date(data_TNC$FECHADEALTA, format = "%d-%m-%Y %H:%M:%S")),]
```

Figure 8: Binding the three databases

The next step was visualise if the data set provided a consistent result for the problem. After the data transformation, and binding the three databases, the output was very close to the desired. Yet, it was possible to spot some inconsistencies between the status of the work orders and the annulation codes. Some work orders, by mistake, came with an annulation code even though the status was "confirmed", meaning it was necessary to null the annulation code in these cases in order to have a consistent output. In that way, was created a double condition that defined the annulation code as NA if the status was "confirmed" or "pending" which is represented by the letters "F", "C" and "I" in figure 8, and simultaneously the annulation code was not null.

```
data_TNC$CODIGORAZONANULACION <- ifelse(data_TNC$ESTADO == "F" & data_TNC$CODIGORAZONANULACION != "", NA,
                                 ifelse(data_TNC$ESTADO == "I" & data_TNC$CODIGORAZONANULACION != "", NA,
                                   ifelse(data_TNC$ESTADO == "C" & data_TNC$CODIGORAZONANULACION != "", NA,
                                     ifelse(data_TNC$ESTADO == "A" & is.na(data_TNC$CODIGORAZONANULACION) == TRUE, "221",
                                      data_TNC$CODIGORAZONANULACION))))
```

Figura 9: Fixing data inconsistencies

The fourth step is programming, where the variables created such as in "*Operador*" are put into proper functions and the result set is compared to the desired output. In this step is when is compared the result of matching the data between "*Operador*" and "*Dados FS*" by the unique ID *MATRICULA* or matching the data by the unique ID *NUMEROORDEN*.

In order to create a consistent and reliable output when merging the two databases, first was created a temporary dataset with all the records of "*Dados*

FS" but only with the work orders ID, the car plate numbers and the date of creation of the opportunity. This new dataset was called "*Cálculo Dados Operador*" and was used only with the purpose of finding the first channel of entrance of each opportunity. In that way, "*Cálculo Dados Operador*" was merged with "*Operador*" by the work order ID, since there were opportunities that did not have a car plate number or the number was not reliable, such as "00-00-00". Considering that, "*Cálculo Dados Operador*" had only five variables: the car plate numbers, the work orders ID, the date of creation of the opportunity and the channel description.

From "*Cálculo Dados Operador*" were extracted all the records with just the car plate numbers that were equal to "00-00-00" and the ones that did not have a car plate number at all, illustrated in figure 10, as "by_FS". The goal of doing this was to find in these cases the customer channel of entrance by the work order number, *NUMERO ORDEN*. Then, in "by_FS" the work orders that were duplicated were grouped considering the earliest date of entry, which allowed to eliminate the potential duplicates that could exist and keeping the oldest entry of each work order ID, as illustrated in figure 10. Because there were still some duplicates, those were also removed.

```
by_FS <- subset(CALCULO_DADOS_OPERADOR, MATRICULA == "00-00-00" | is.na(MATRICULA))

by_FS <- by_FS %>% group_by(NUMEROORDEN900) %>% filter(FECHADEALTA==(min(FECHADEALTA)))
by_FS <- by_FS[!duplicated(by_FS$NUMEROORDEN900),]
```

Figure 10: Grouping data by work order ID and earliest entry

The same procedure was repeated but for the car plate numbers, which means that from "*Cálculo Dados Operador*" were extracted the car plates different from "00-00-00" and that were not null as "by_MATRICULA" and filtered the duplicates by the earliest entries of each.

After, the database “*Dados FS*”, illustrated as “data_TNC” in figure 11, was merged first with the car plates numbers, *MATRICULA*, and after with the work orders IDs, *NUMERO ORDEN*.

```
data_TNC_NEW <- merge(data_TNC, by_MATRICULA, by = "MATRICULA", sort = F , all.x = T)
data_TNC_NEW <- merge(data_TNC_NEW, by_FS, by = "NUMEROORDEN900", sort = F, all.x = T)
```

Figure 11: Merging "Dados FS" by car plate numbers and work order ID

Finally, the database was tidied by creating only one column for the channel, which involved keeping the channel descriptions that came from “by_MATRICULA” and filling the records in that column that were empty with the respective channel description from “by_FS”, as illustrated in figure 12, and eliminating the duplicated variables that came from the “by_FS” and “by_MATRICULA” when merging with “*Dados FS*”.

```
data_TNC_NEW <- data_TNC_NEW %>%
                mutate_all(as.character) %>%
                mutate("Canal 2.0" = ifelse(is.na(Canal.x), Canal.y, Canal.x))
```

Figure 12: Filling empty values with respective data from work order ID

The final step is communication meaning the result must be clear and understandable. After getting the desired output for the database, it is in this step that starts the dashboard development.

4.2.2. Power BI: Dashboard Development

The analysis to the KPI, as mentioned before, was done through pivot tables and nothing else. Because of that, it was necessary a dashboard that allowed to spot all variables that could lead to potential red flags or give some hints of possible reasons for some results, since there are many variables that can affect conversion.

As mentioned in subchapter 3.3 the dashboard structure has into consideration the strategic, tactical, and operational point of view in terms of decision-making in Operations Management. Considering that, there are in total five pages in this dashboard which are *Overview*, *Pendentes*, *Anuladas*, *Leak Model* and *CCC*. All the pages with exception of *CCC* has in total nine slicers, all the same in the fourth pages.

The strategic page called *Overview*, figure 13, answers the more general questions such as how many opportunities were open till the present moment and through which channel and which type of clients. It shows how many days are the clients waiting in order to get an appointment and, the TNC. The cards that answer how is the KPI have a colour formatting that if the KPI reached the target or surpassed it then it is green, if it is close to achieve it is yellow and if it is far from achieving the colour will be red. It was used circular doughnut charts in order to understands how the whole of the opportunities is distributed by status, channel, and type of client.

Figure 13: TNC Overview

The second page, *Pendentes*, is the operational page meaning it is where it is possible to act and make daily decisions in order to control the conversion since it is the opportunities that are still pending and are not yet confirmed or annulated.

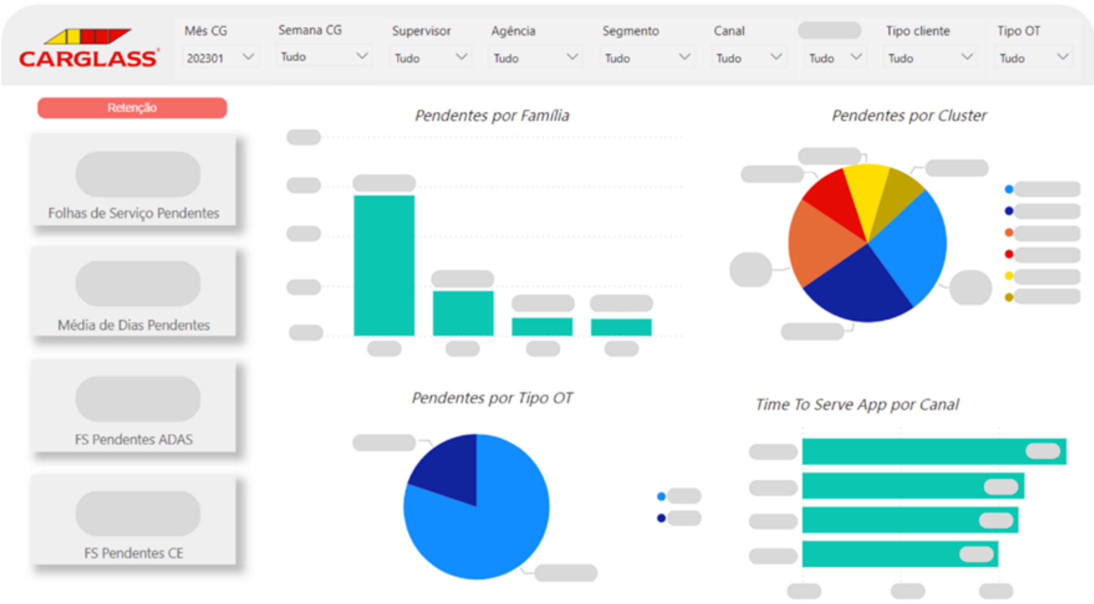

Figure 14: Pendentes

In this page, figure 14, was used circular charts in order to understand how the whole of the pending opportunities are distributed per cluster and per work order type. The bar charts were chosen with the goal of spotting potential red flags when comparing the time to serve per channel or the time to serve per type of windshield.

The *Anuladas* page is the tactical page since it's about analysing the opportunities and the reason for it and develop mid-term actions to improve conversion considering the results. This page has three cards in which tells how many opportunities were annulated and of those, how many had an appointment. It also has doughnut charts in order to understand how those annulated opportunities are distributed by channel and per type of client. The *Leak Model* page is an auxiliar to the *Anuladas* page since it has a decomposition tree that allows to understand through what region, channel, detail of channel is the principal reasons for annulation.

Finally, the *CCC* page was developed with the goal of analysing the conversion of the *Contact Centre* specifically and various factors that can influence it. A gauge chart was used so the supervisor of the *Contact Centre* could follow the progress of the conversion and the colour of the bar changes accordingly to the status of the KPI. Three cards were also used with the goal of explicitly showing how many opportunities were converted, how many were lost and how many can still be converted in order to reach the goal of conversion. A line chart was used so it is possible to spot possible trends in demand.

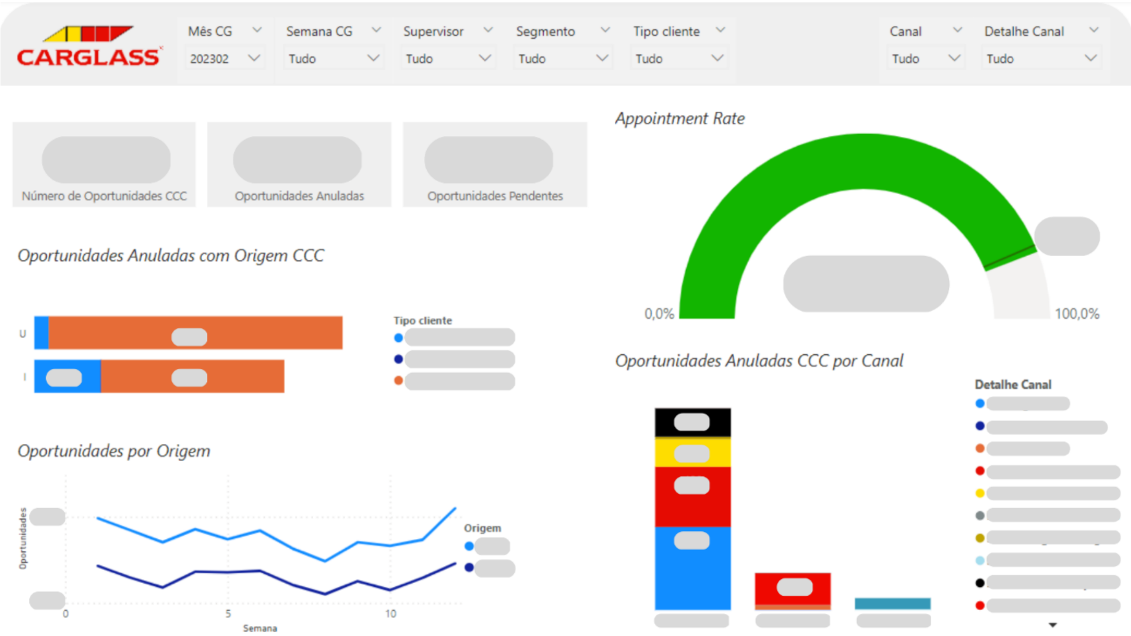

Figura 15: CCC

It was created several measures such as the TNC and *Appointment Rate*, which can be found in the attachments. It was also created many data groups in order to create the measures and some charts more easily such as the doughnut chart in *Anuladas* that shows of the total opportunities lost that had an appointment, in how many days were those appointments, and the cases that had more than 6 days were grouped into a group of called "6 or more days".

The dashboard was also adapted for the mobile version having in mind the possibility of, in the future, acquiring Power BI Pro licences for the users.

4.3. Final Report

To demonstrate the actual existence of progresses in the pre-processing of the database and analysis of the KPI, it is required to analyse all the point mentioned in subchapter 4.1. with the application of the improvements mentioned in subchapter 4.2.

Looking at the data pre-processing stage, it was possible to conclude that many records were not being correctly identified as opportunities and annulated as duplicates and therefore not considered to correctly measure conversion. With the implementation of the R Script, the identification of duplicates and opportunities became precise and consistent since it ran throughout the same process it had in base report but this time with all the steps automatised and with precise and well-defined functions. Besides that, before developing the R Script, the preparation of the database for the analysis took, at least, a full morning and could sometimes even take a whole day. After the development of the R Script, pre-processing the data take 2 minutes maximum, considering that the part that is still more time-consuming is downloading the excel files before running the R Script.

The second cycle, dashboard development, was the creation of a totally new dashboard from scratch. The dashboard allowed to actual see patterns in data instead of just numbers in a pivot table. It also allowed to answer quickly to questions regarding the more general side of the KPI but also more specific questions even regarding the performance indicators that affect it. Being the dashboard in Power BI, the company saw utility for the operations department in using the mobile features since regional supervisor managers have an active job and usually few times to seat in front of a computer to gather information and analyse it. With, while before to access information could be time-consuming and not always convenient, nowadays, users can access the information through their phones and take right away some convenient insights. Before the creation of the dashboard, analysing more deeply the KPIs related with the CCC was not easy and did not give much information. With the creation of the dashboard, the supervisor can now work on its particular conversion, *Appointment Rate*, and report more visually the KPI status to the team. It is also easier with the use of the decomposition tree track possible problems in conversion per region or per channel while before was necessary to manipulate a pivot table to try to extract any insights that could correlate the two of variables.

Considering all the improvements mentioned in subchapter 4.2, the results obtained in matters of improvement in data pre-processing with the R Script and data visualisation with the Power BI dashboard, the improvements were mostly in efficiency in preparing the data and, consequently, faster decision-making; since with the R Script the data pre-processing, instead of taking a whole morning, takes only 2 minutes and, with the Power BI dashboard it is faster and easier now to spot trends or potential problems that may be affecting the KPI. Those results were aligned with the literature review that focused mainly on how business intelligence tools can indeed improve KPI monitoring and, therefore, decision-making by developing the dashboard, for example, considering the strategic, tactical, and operational decision-making levels and following the big data project lifecycle was key to guide the process of developing the final report and its improvements.

Fifth Chapter

5. Conclusion

The goal of this dissertation is to use Business Intelligence to improve KPI monitoring in Operations Management, which in this project focused mainly on improving data pre-processing and data visualization relying on BI tools, R Studio and Power BI. The KPI in question is TNC from Carglass Portugal, where the internship that drove to this research took place.

5.1. Final Conclusions

Looking at all the specific goals defined previously, all of them were successfully achieved, which lead to the achievement of the main objective of improving KPI monitoring in Operations Management.

After the development and implementation of everything described in the previous chapter, there were also some observations that needed to be considered such as:

With the implementation of the R Script, it was easier and more precise to detect duplicates and find the channel of entrance of each opportunity.

By developing the TNC dashboard, became more visual analysing the KPI and therefore, easier to understand some patterns, trends, and potential problems.

Besides the development of the R Script, that improved significantly the data pre-processing, it was still needed to export the output for an excel file to create other variables that were dependent of other excel files that were got by e-mail every week and without the possibility of extracting with queries.

Because of the previous statement, it was not possible to use as the dashboard source the R Script, having the need of weekly change the data source for the new weekly excel file.

5.2. Major Contributions

To explain the actual improvements with this project and the major contributions, it is easier to divide it in two points of view: operations controller and operations team.

For the operations controller, there was an improvement in data pre-processing, which became easier, faster, and more precise, and in data visualisation and, consequently, data analysis since now there is an actual visual representation of the KPI and the variables that affect it, which allows to take faster conclusions and take actions faster.

For the operations team, it's easier now to access information and also make some decisions since before they needed to access the information through a computer in an excel file and, now they can do it just by opening the dashboard on their mobile phones in the Power BI app.

For both points of view, there is also some common advantages considering before the information provided on the pivot tables was dependent on the filters of each table that allowed to analyse the specifications mentioned previously such as per type of client, channel specification and region, and now with the Power BI dashboard there isn't the risk of accidentally change the information since it's well defined with actual measures and controlled considering just the editor can change anything on the dashboard. It is also easier now for each supervisor and the operations controller to communicate and report results for their respective teams.

5.3. Recommendations for future work

Regarding future work for this project at Carglass Portugal, there are some improvements and tasks that can be done:

- Make the data pre-process 100% on R Studio, as the R Script can then be used directly as data source of the Power BI dashboard.
- Create an automated report based on the dashboard with Power Automate.

The first improvement would allow the operations controller to not worry at all with the data pre-processing and having automatised every single step of the data preparation. The creation of automated reports would also help to report results faster and more efficiently and would be another way of allowing the information arrive to the supervisors more directly.

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Attachments

Measure	Description
Total Net Conversion	TNC = divide(CALCULATE(COUNT('Dados FS'[NUMEROORDEN]),'Dados FS'[Estado FS]="Facturada"),CALCULATE(COUNT('Dados FS'[NUMEROORDEN]),ALL('Dados FS'[CODIGOTIPOORDENTRABAJO])))
Appointment Rate	App Rate = divide(CALCULATE(COUNT('Dados FS'[NUMEROORDEN]),'Dados FS'[FS vs Orçamentos]="Folhas de Serviço", 'Dados FS'[Origem] = "CCC"),CALCULATE(COUNT('Dados FS'[NUMEROORDEN]),ALL('Dados FS'[FS vs Orçamentos]), 'Dados FS'[Origem] = "CCC"))

Attachment A: Dashboard Measures