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TRABALHO FINAL DE MESTRADO
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REVOLUTIONIZING INSURANCE ANALYTICS: BI APPROACH TO REPORTING

MARIANA FILIPA TRAVASSOS MARTINS

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LIST OF ABBREVIATIONS

BA – Business Analytics

BI – Business Intelligence

DAX – Data Analysis Expressions

DL – Data Lake

DW – Data Warehouse

ETL – Extract, Transform, Load

KPI – Key Performance Indicators

MFW – Master's Final Work

YTD – Year-to-date

ABSTRACT

In a data-driven world shaped by rushing digital transformation, the insurance industry faces growing pressure to modernize its reporting practices and leverage BI as a competitive advantage. This MFW explores a real-world implementation of an automated BI solution within a Portuguese life insurance company affiliated with a bank. The project addresses critical inefficiencies related to a fragmented and predominantly manual reporting process, that limits performance monitoring and decision-making.

The solution designed and implemented a centralized reporting model, through the development of a modular system architecture, automating the reporting pipeline using scheduled tasks. It resulted in a dashboard tailored to the organisation's financial and risk product lines, enriched with KPIs, trend indicators, and dynamic filters, allowing a more autonomous, self-service data exploration. Furthermore, the project improved report readability and stakeholder engagement by introducing advanced data visualization techniques and a mobile-optimized layout.

This research contributes to a broader professional understanding of the application of BI in the insurance sector, providing a detailed case study that highlights both the opportunities and challenges of digital transformation through data-driven reporting solutions.

KEYWORDS: Business Intelligence; Reporting Automation; Insurance Analytics; Power BI; Data Visualization.

RESUMO

Num mundo orientado por dados e moldado por uma rápida transformação digital, o setor segurador enfrenta uma pressão crescente para modernizar as suas práticas de relatórios e tirar partido de BI como uma vantagem competitiva. Este trabalho explora a implementação real de uma solução automatizada de BI numa seguradora portuguesa do ramo vida, afiliada a um banco. O projeto aborda certas ineficiências associadas ao processo de relatórios fragmentado e maioritariamente manual, que limita a monitorização de desempenho e a tomada de decisão.

A solução consistiu no desenho e implementação de um modelo centralizado de relatórios, através do desenvolvimento de uma arquitetura modular do sistema, automatizando o fluxo de dados com rotinas agendadas. O resultado foi um *dashboard* adaptado a produtos financeiros e de risco da organização, enriquecido com KPIs, indicadores de tendência e filtros dinâmicos, permitindo uma exploração de dados mais autónoma. Além disso, o projeto melhorou a legibilidade dos relatórios e o envolvimento dos *shareholders*, ao introduzir técnicas de visualização de dados e um layout otimizado para dispositivos móveis.

Esta investigação contribui para o entendimento profissional sobre a aplicação de BI no setor segurador, oferecendo um estudo de caso detalhado que evidencia tanto as oportunidades como os desafios da transformação digital através de soluções de relatórios orientadas por dados.

PALAVRAS-CHAVE: Business Intelligence; Automação de Relatórios; Análise de Seguros; Power BI; Visualização de Dados.

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1. INTRODUCTION

In today's data-driven economy, organisations are increasingly leveraging Business Intelligence (BI) to transform vast amounts of data into actionable insights, thereby enhancing decision-making and operational efficiency. BI is an ongoing investment for companies seeking accurate information to make the right decisions, so that the value generated significantly exceeds the associated costs (Arnott et al., 2017). Insurance companies, particularly the ones affiliated with banks, are characterized by their reliance on data and are well-positioned to benefit substantially from BI implementations, enabling them to respond swiftly to market dynamics and customer needs (Ellili et al., 2023).

The insurance industry has traditionally relied on manual processes and legacy systems for data analysis and reporting, often resulting in inefficiencies, delayed insights and limited scalability. Therefore, the advent of digital technologies has led to exponential data growth in volume and complexity, revealing a necessary shift towards automated and interactive reporting solutions. Manual report generation is time-consuming, besides also being prone to human error and inconsistencies. Furthermore, the lack of integration between disparate data sources complicates the reporting process, leading to inefficiencies and reduced data accuracy (Huang et al., 2022).

This Master's Final Work (MFW) presents an applied project focused on automating BI processes within a real-world context – a Portuguese life insurance company affiliated with a banking institution – intending to optimize data-driven decision-making. The project was introduced in response to identified operational inefficiencies in the organisation's current reporting practices, particularly those associated with manual routine and fragmented data sources. The main initiatives aimed to streamline the report and dashboard development process, reducing production time and enabling analysts to focus on higher-value tasks. In parallel, it targeted the clarity and readability of reports by improving their visual appeal, thereby making insights more accessible. Lastly, a further objective was regarding the system performance, since the IT department addressed concerns about frequent and resource-intensive access to the operating system, which impacts overall efficiency. The expected output of this MFW is a fully functional and automated Power BI dashboard tailored to the company's financial and risk products.

A significant component of the project involves the exploration and evaluation of various features of Power BI – a leading BI tool developed by Microsoft – to access its capabilities, functionalities, and relevance for data analysis and visualization in dynamic business environments. Integrating BI tools offers a viable solution to these challenges by streamlining data management processes, enhancing analytical capabilities and delivering real-time insights, ultimately ensuring consistency and accuracy (Adeniran et al., 2024).

This MFW is organized into six chapters, each serving a specific purpose to comprehensively address the automation of BI processes in the insurance sector. The following section establishes theoretical foundation by providing an overview of data-driven organisations, data architecture and key BI concepts, while emphasizing the growing relevance of BI tools in transforming data into actionable insights, with a focus on their relevance in the insurance industry. Chapter 3 provides the project context, presenting an overview of the organisation, its current infrastructure and reporting processes, and the key challenges and needs that motivated the development of a more dynamic reporting solution. Chapter 4 outlines the structure of the reporting solution, regarding the system architecture, data sources and technologies selected for implementation. Chapter 5 continues by describing the implementation process, from problem understanding and data preparation to the development of the solution. In this chapter, the project's results are presented, complemented by the feedback analysis. The final chapter summarizes the key findings and their implications for the insurance industry, discussing the limitations encountered during the study and suggesting avenues for future work in the field of BI automation.

Building upon the theoretical principles of BI and data-driven decision-making presented in the literature, this MFW applies these concepts in a real business context, demonstrating how analytics can be leveraged to answer real-world inefficiencies in reporting and visualization. This link further reinforces the relevance of the documents explored in the following chapter.

2. LITERATURE REVIEW

The present section establishes a theoretical foundation on how data and BI are utilized to visualize business performance through dashboards, ensuring a comprehensive understanding of the concepts and technologies that support data-driven decision-making. Furthermore, it contextualizes the relevance of these topics within the insurance industry, where data plays a crucial role in optimizing risk assessment and enhancing operational efficiency. Although there is limited discussion about the practical barriers that organizations face when automating these models, this reality highlights the importance of applied research – a focus point reflected in this MFW.

2.1. Data-Driven Organisations

A data-driven organisation utilizes data strategically to enhance its performance and drive business growth. This concept involves the adoption of suitable tools and technologies, as well as the development of employees' skills, the establishment of efficient processes, and the cultivation of an organisational culture that supports data-driven insights and their effective implementation (Anderson, 2015).

Morrow (2022) identifies five key pillars that are essential to a data-driven organisation:

1. **Organisational Strategy –** Integrating the organisation's data strategy with the overall business strategy is important to align data initiatives with the company's objectives, being a complement to decisions and actions that drive success.
2. **Leadership –** Strong leadership is a key factor in the successful execution of the data strategy, providing the necessary resources to support the data-driven initiatives. Leaders in an organisation need to motivate and guide employees at all levels to embrace the power of data in decision-making processes.
3. **Data Literacy –** Employees must have the ability to interpret, analyze and understand data, allowing a culture where teams are capable of converting it into meaningful insights.
4. **Technology –** The right digital tools and systems enable organisations to store and visualize the high volume of data from multiple perspectives, facilitating employees across departments to access and derive informed conclusions.

5. **Organisational Culture –** The culture of the organisation can influence how the shift towards a data–driven approach occurs, since the workers must be willing to change and adopt new practices and technologies.

These five pillars establish the foundation of a successful data-driven organisation, ensuring that data is used to drive business performance effectively. According to Altdorf (2024), this transition is effectively supported by reporting tools for operational work management, which offer advanced visualization and reporting features that improve the accessibility and usability of data.

2.2. Data

Data is considered the raw material for information, which has little intrinsic value in its unprocessed state. However, after being processed and structured, it can become knowledge that supports decision-making processes. There are three primary data categories classified by structures. Structured data is highly organized and easily searchable, since it follows a predefined schema, typically stored in relational databases. In contrast, unstructured data require advanced processing and analysis techniques, due to the lack of a fixed format and include diverse formats such as text and multimedia content. Serving as a middle ground between these two categories, semi-structured data incorporates organisation markers that provide some level of order while lacking a strict tabular format. Recognizing the distinctions between data types is fundamental for implementing data management strategies that support integration, usability and analytical insights across various business functions (Laursen and Thorlund, 2016).

According to Anderson (2015), for data to generate trustworthy insights without leading to misinterpretations, it must fulfil several quality requirements, including accessibility, accuracy, coherence, consistency and timely availability for analytical purposes. Additionally, ensuring that data can be linked with other datasets through unique identifiers, such as primary keys or IDs, enhances integration and usability across various business functions.

2.2.1. Data Architectures

Data architecture provides a systematic and scalable framework for organizing data storage, processing and retrieval, being fundamental to ensuring efficient data management, facilitating integration across systems and promoting broad accessibility within the organisation (Nambiar and Mundra, 2022). Furthermore, robust data architecture is crucial for preserving data integrity and guaranteeing compliance with data governance and regulatory policies, while also enabling organisations to extract meaningful insights from their datasets (Sawadogo and Darmont, 2021). Within this architecture, Database Management Systems (DBMS) – including platforms as SQL Server, PostgreSQL and Oracle – serve a core function by providing the technological infrastructure for storing, accessing and managing structured data. These systems act as the operational backbone of the architecture, enabling seamless integration across systems and sustaining the data flows required for effective BI initiatives (Coronel and Morris, 2015).

Companies increasingly encounter challenges related to data storage and quality management, highlighting the necessity for comprehensive governance frameworks that maintain data consistency, security and reliability (Viljanen, 2020). Therefore, centralized data management solutions – such as data warehouses (DW) and data lakes (DL) – play a critical role in standardizing processes and mitigating risks associated with data redundancy, inaccuracies and unauthorized access. These systems enhance the integrity and trustworthiness of organisational data, thereby maximizing the value derived from BI and advanced analytics initiatives.

2.2.2. Data Warehouses and Data Lakes

DWs were introduced in the 1980s as a solution to manage data flow in decision-support environments, empowering business leaders with reliable information for analysis derived from a unique source. It serves as a centralized and scalable repository that systematically collects, standardizes, and maintains structured data from a variety of internal and external sources, creating a single, unified dataset that guarantees consistency and accessibility. The DW framework follows an extract, transform, and load (ETL) process that integrates data from operational systems into specialized processing units, forming the foundation for data mining, and reporting (Nambiar and Mundra, 2022).

The implementation of DWs carries numerous advantages. Not only does it help reduce the reliance on manual processes that are typically tied to primary organisational systems, but it also alleviates the strain on source systems by offloading the heavy demands of daily reporting and enabling seamless data integration across departments. This consolidation enables having a history that facilitates the tracking of data changes over time, ensuring that information is preserved even when source systems modify or delete records. Building on the centralized data infrastructure provided by DW, organisations often leverage data marts – business-specific subdivisions of DW – to further optimize data accessibility and relevance for teams or departments, as they are designed to store and manage data tailored to users' requirements. By focusing on targeted datasets, data marts facilitate access to information that is most pertinent to specific operational needs without the complexity of navigating the more generalized dataset within the broader DW, enhancing user experience (Laursen and Thorlund, 2016).

The concept of DLs, on the other hand, emerged as a response to the limitations of data marts, where DL represents a modern enterprise data management solution designed to handle raw, unprocessed data at scale, since the rapid expansion of diverse and high-volume data sources made traditional approaches inefficient for managing semi-structured and unstructured data (Nambiar and Mundra, 2022). It serves as a centralized repository for data in its original form, since DL operates on a schema-less write and schema-on-read approach. It provides organisations the flexibility to store data without predefined structures and to apply dynamic data models when querying, enabling the extraction of insights without being limited by rigid schemas. Initially, DL were often associated with Hadoop-based technologies due to their cost effectiveness in storing and processing raw data. However, the landscape has evolved with proprietary cloud-based platforms becoming increasingly popular for DL implementations, offering scalable and efficient solutions for enterprise data management (Sawadogo and Darmont, 2021).

The primary advantages of DLs include their scalability, because they enable the processing of large datasets across distributed clusters using simple models and their ability to integrate high-velocity streaming data with vast volumes of historical information. They also facilitate advanced analytical processing and immediate access to raw data without requiring pre-modelling (Singh & Ahmad, 2019).

2.3. Business Intelligence

BI refers to a large-scale system composed of a phased set of processes, technologies, and tools designed to systematically collect, integrate, analyze and present business data. In essence, it involves the entire information lifecycle – from data acquisition and processing to dissemination, ensuring that relevant and accurate information is available to stakeholders at all levels of the organisation (Arnott et al., 2017). The core purpose of BI is to consolidate substantial amounts of data from various sources, transforming raw data into actionable insights, thereby reducing uncertainty and enhancing the quality of organisational decisions (Adeniran, 2024).

A typical BI system requires several key processes, including data warehousing, data mining, reporting and analytics tools. Data warehousing centralizes data from multiple sources into a single repository, while data mining enables organisations to identify patterns, correlations and irregularities in large datasets. The reporting layer involves dashboards and data visualization tools, which improve the ability to interpret complex information quickly. BI requires structured data storage for effective analysis. Although BI solutions can be built without a DW to compile and store data, the alternatives are prone to errors, including data integrity issues, difficulty in tracking data sources and lack of historical data storage (Kainulainen, 2020).

The implementation of BI solutions relies on an underlying IT architecture capable of supporting a variety of software systems, ensuring long-term adaptability in response to the continuous evolution of technological and business requirements. A critical aspect in this context is the choice of deployment models, since organisations must assess whether to adopt on-premises infrastructures, cloud-based platforms, or hybrid approaches that combine both, depending on their operational needs and strategic priorities (Viljanen, 2020).

On-premises architecture involves hosting physical servers either internally or managed by external providers, offering usability without internet connectivity and greater control over data security. However, this approach has limited scalability, and it requires substantial investment in hardware infrastructure, ongoing maintenance and the implementation of dedicated security measures. In contrast, cloud-based BI solutions are preferred due to their small initial investment and rapid deployment, also allowing organisations to adjust storage capacity and processing power as needed. Besides that, the service provider oversees the system maintenance and security, minimizing the operational burden on internal teams. To leverage the strengths of each deployment method, hybrid models present a balanced alternative tailored to specific strategic and operational requirements. To fully leverage the strengths of each deployment method, hybrid models offer a balanced alternative tailored to specific strategic and operational needs (Munk, 2019).

In addition to its core components, BI systems are also distinguished by their ability to automate a wide range of data processing tasks, operate independently of local computing infrastructure and improve comprehension through advanced data visualization tools (Ilvonen, 2019). BI visualization helps reveal implicit trends and patterns by transforming raw data into comprehensible graphical formats, which makes it quicker to understand and convert to knowledge (Jun, 2020).

BI and Business Analytics (BA) share similarities but differ in their focus and methodology. While BI provides descriptive insights into past events and current trends, essential for understanding organisational performance overtime, BA incorporates statistical modelling, machine learning, and predictive analytics to forecast trends and optimize future outcomes, adding a forward-looking element to the analysis (Paradza and Daramola, 2021).

The evolution of BI has been driven by a continuous adaptation to the changing technological landscape and the growing complexity of organisational needs, evolving to meet the demands of modern businesses. This progression can be categorized into three distinct phases, each marked by significant advancements in technology and its application in business environments:

- **BI 1.0 –** The first phase, which emerged in the 1990s, was centered on structured data from internal sources, relying heavily on statistical methods and basic reporting tools. It focused on improving internal decision-making processes through the systematic analysis of historical data.

- **BI 2.0 –** The advent of new web technologies and the advancements in DW techniques lead to an evolution towards the analysis of unstructured data, especially from web-based sources. This phase also witnessed the introduction of collaborative features and improved data integration capabilities, making BI more accessible to a broader range of users within organisations and promoting a more interactive approach.
- **BI 3.0 –** The most recent stage integrates big data, mobile analytics, the Internet of Things (IoT) and cloud computing. It enhances the accuracy of insights and supports dynamic, real-time analytics, empowering organisations to respond swiftly to changing market conditions and operational challenges.

The purpose of a BI process is to produce valuable knowledge and insights through the transformation of raw data and information, while also integrating prior knowledge and intelligence. This process can be carried out through ad-hoc analysis or as part of a more continuous approach. The continuous BI process can be viewed as a cycle, allowing organisations to adapt to changing data environments and evolving business needs, ensuring that the insights generated remain relevant and actionable over time. Importantly, each phase builds upon the achievements of the previous one, with the integration of new technologies continuously enhancing the value and effectiveness of BI tools in both business and IT environments (Kainulainen, 2020). Despite the broad consensus regarding BI's capacity to enhance decision-making, this MFW adds value by applying these theoretical constructs within a business context – particularly in a highly regulated industry. It demonstrates how BI principles can be adapted to improve data flow and automation without requiring large-scale infrastructure changes.

BI has emerged as a strategic asset, providing a wide range of benefits to organisations aiming to enhance their performance, competitiveness and decision-making quality. Nevertheless, BI's effective use depends on the development of technological systems tailored to the specific needs and infrastructures of each organisation (Niu et al., 2021).

A key advantage of BI relies on its capacity to generate accurate and real-time insights that inform both strategic and operational planning (Abu-AlSondos, 2023). Through the integration of data from multiple sources, BI platforms improve accessibility and foster collaboration across organisational departments, enabling stakeholders to reach relevant information in a timely and consistent manner. In addition to improving information flow, BI minimizes the need for manual workload, contributing significantly to cost reduction by automating reporting and analytical processes (Gonçalves and Campante, 2023). Furthermore, by applying advanced analytical techniques, BI tools can effectively uncover anomalies and strengthen both financial and operational safeguards, supporting fraud detection and risk management efforts while empowering organisations to gain a competitive advantage by responding swiftly to market changes and evolving customer demands (Viljanen, 2020).

Despite its many advantages, the adoption of BI systems presents several challenges, as integrating these systems with existing IT infrastructures entail significant investments in software, infrastructure and personnel training, besides being technically demanding. Moreover, maintaining high data quality standards is essential to ensure that the insights generated are accurate, consistent and actionable (Kainulainen, 2020). However, the success of BI implementation is dependent on organisational culture, highlighting the importance of minimizing employees' resistance to change by investing in training programs and different management strategies (Gonçalves and Campante, 2023).

BI is rapidly advancing in response to emerging technologies, such as the integration of Artificial Intelligence and Machine Learning into BI tools, that strengthen predictive analysis and automating insights. Additionally, real-time analytics is becoming increasingly prevalent, allowing businesses to process data instantaneously and make timely strategic adjustments, which transforms the operational response. These advancements underscore that the future of BI is towards more intelligent, responsive and user-oriented systems, reinforcing its role as an essential enabler of data-driven innovation and strategic agility.

2.3.1. BI in the Insurance Industry

The insurance industry heavily relies on BI, which serves as an essential tool in supporting core operational and strategic functions. Given the sector's inherently data-intensive nature, it demands robust systems capable of processing and managing vast volumes of complex and sensitive information. A structured BI architecture is critical for insurance companies to integrate multiple data environments – including DW, DL and real-time analytics platforms. The capacity to analyze historical claims data, predict policyholder behavior and detect fraudulent activity more effectively highlights the strategic role of BI in improving decision-making processes across all organisational levels (Viljanen, 2020).

However, the successful deployment of BI systems in insurance also depends on overcoming specific organisational challenges, that are generally classified into internal, external and technical factors. Internally, the effective use of BI tools can be limited by a lack of proper training, along with employee resistance to adopting new solutions that alter established workflows. Moreover, BI effectiveness relies depends on the quality, accessibility and integration of data generated by operational systems – which serve as the primary sources of transactional data for BI environments. Externally, the reliance on IT consultants may restrict the support required to fully integrate BI with core organisational processes. On the technical side, concerns related to data privacy and security pose significant obstacles, alongside challenges such as ensuring data governance, addressing compatibility with legacy systems, and maintaining high standards of data accuracy and security throughout the BI lifecycle (Gonçalves and Campante, 2023).

Insurance companies must develop an organized BI strategy, combined with investments in continuous employee training and technological infrastructure, essential to foster a data-driven culture and unlock the full potential of BI in enhancing competitiveness, and operational agility in this industry.

2.4. Data Visualization

Data visualization provides a summary of the data through graphical forms, such as diagrams, charts, and more, granting an intuitive and efficient way of presenting information. Since the information is displayed on dashboards tailored to the user's specific needs, it helps decision-makers to process and understand data faster than when presented in raw numerical or textual formats, due to the reduced cognitive effort required for interpretation (Bikakis, 2018). Moreover, the impact of data visualization extends beyond merely simplifying data interpretation. It represents a central component of BI systems by facilitating the extraction of insights and the identification of patterns that might otherwise remain unnoticed (Ruan et al. 2017). Data visualization is the process of presenting data in graphical formats using user-friendly tools that facilitate real-time data examination and analysis. The visual representations within these platforms convey analytical insights to the audience in an accessible manner. However, to extract meaningful knowledge from large datasets, it is crucial for the data to be presented in a logical and structured way. Proper grouping and segmentation of data points enhance the ability of users to identify key areas of interest, enabling them to focus their attention on the most relevant and significant patterns (Mohammed et al., 2022). Furthermore, although continuous training of teams is crucial for organisational success, even individuals with limited expertise in data analysis can comprehend the significance of data more effectively through visuals. This fosters a broader understanding of information across all organisational levels, thus promoting a more inclusive and informed decision-making environment (Barua et al., 2019).

The design of effective data visualizations is equally important as the data itself. As Few (2009) emphasizes, visualization is not merely about displaying the data, but also about ensuring that the presentation's design assists comprehension, as visual elements, including color schemes, chart types, layout and visual hierarchy, each one serving a distinct role and contributing to the clarity of the visualization. However, different types of data require different visualization methods, while some work well for specific kinds of data, others may fail to communicate the intended message.

The emergence of Big Data presents unique demands in terms of scalability, usability and clarity, while the growing volume of data represents a strategic asset, it also requires the appropriate tools to manage and interpret it. Data visualization enhances the accessibility and comprehension of data, even when dealing with large, heterogeneous datasets. The ability to manipulate variables and apply filters in real-time streamlines the extraction of insights more efficiently (Altdorf, 2024).

2.4.1. Dashboard and Key Performance Indicators

In the dominion of BI, dashboards have emerged as an essential instrument that is defined as a collection of data visualizations designed to provide a widespread view of critical business metrics in a user-friendly interface. Dashboards serve as centralized interfaces that consolidate data from diverse sources and present the performance indicators in a unified view, fostering a proactive approach to business management. Altdorf (2024) highlighted the importance of aligning displayed metrics with organisational objectives to ensure efficient monitoring of progress toward goals, besides structuring the system into multiple screens to allow users to focus on specific objectives without feeling overwhelmed by excessive information.

Key performance indicators (KPIs) serve as the cornerstone of dashboards, facilitating the development of visual reports that focus on the actual performance of a business within its specific environment, along with better performance tracking (Lousa et al., 2019). By offering quantifiable measures that reflect critical aspects of organisational performance, it serves as a guide to organisations to track their progress toward achieving strategic objectives. KPIs should adhere to the SMART criteria – Specific, Measurable, Achievable, Relevant, and Time-bound – to effectively guide decision-making. These indicators provide valuable insights by measuring progress over time and comparing current performance against predefined targets. In addition to monitoring, they also function as diagnostic tools for identifying anomalies or deviations from expected outcomes, thereby enabling organisations to promptly identify and address potential issues within their processes.

The integration of KPIs into dashboards enhances their utility by providing clear, quantifiable measures of performance with interactive features that allow users to filter and drill down into data for more detailed analysis. This interactivity supports diverse user roles, from executives seeking strategic overviews to managers requiring detailed operational insights (Gonçalves and Campante, 2023). The visual nature of dashboards makes it easier for managers to spot trends and patterns that may not be immediately obvious in raw data, facilitating faster and more accurate decision-making. This is particularly important in industries where operational efficiency, customer satisfaction and financial performance are closely monitored.

2.5. Benefits of Reporting Automation and Implementation Challenges

In today's data-driven business environment, reporting automation aims to streamline the processes of data collection, analysis and reporting, as it minimizes manual effort, reduces the risk of human error and also allows teams to focus on strategic initiatives rather than repetitive tasks (Adeniran, 2024). The ability to automatically update reports ensures that they reflect the most current data, enabling organisations to make data-driven decisions based on the latest available insights (Singh et al., 2023).

The analysis of the company under study aligns with the literature, which indicates that manual reporting processes limit analytical capacity and extend decision cycles. Automating these processes allows the theoretical benefits identified in the literature to be translated into tangible improvements in efficiency and reliability. However, teams must ensure that the quality of the data being reported remains high, in order to prevent reports based on inaccurate or incomplete information.

3. PROJECT CONTEXT

3.1. Organisational Overview

The case company is a life insurance provider affiliated with a bank, offering tailored products to both individual and corporate clients. It operates in a highly competitive sector, where, according to data released by the Portuguese Insurance and Pension Funds Supervisory Authority (ASF) in December 2024, the top three insurers collectively hold approximately 58% of the market share. Competing in the remaining segment, the organisation is under constant pressure to deploy efficient strategies to attract and retain clients while ensuring operational efficiency.

In this context, the company operates with a business model oriented towards delivering client-specific solutions, leveraging its close ties to the banking sector to enhance customer reach and trust, since it is an exclusive distributor of its products. However, the competitive environment, intensified by increasingly demanding regulatory frameworks and evolving customer expectations, emphasizes the urgent need for data-driven decision-making processes. In response to these challenges and opportunities, the organisation has initiated a transformation process aimed at strengthening its data management capabilities and modernizing its reporting infrastructure in a specific department. This MFW contributes directly to that initiative by designing and implementing an automated BI solution focused on enhancing the organisation's reporting procedures. Its main objectives include reducing manual reporting effort, increasing data accessibility and reliability, and improving the clarity and interactivity of dashboards. The project is an integral part of this strategic effort to optimize internal processes and reinforce its competitive positioning within the dynamic life insurance sector, since the sentiment of inadequacy regarding reporting mechanisms and advanced analytical tools prevailed internally.

3.2. Current BI Infrastructure and Reporting Process

The current reporting infrastructure is characterized by a predominantly manual and fragmented workflow, where the data is manually extracted from multiple internal and external sources, that often require considerable consolidation and standardization procedures. Reports are typically developed in Excel, with both Excel workbooks and Microsoft Access databases serving as the primary repositories for storing intermediate and finalized data outputs. To generate a wide variety of outputs and ensure their accuracy, these manual processes necessitate the involvement of individuals with deep domain expertise – covering not just the underlying data but also the specific logic and structure of each report.

Despite the presence of some useful macros within the spreadsheets, many KPIs and business insights are still generated through time-consuming and resource-intensive processes. The resulting reports – including static screenshots, Excel files, PDFs and PowerPoint presentations – are then distributed across the organisation via email or published on the intranet.

The department manages an extensive portfolio of recurring reporting processes, which vary in frequency and complexity. In addition to these routine responsibilities, the team is also responsible for addressing several ad hoc requests, further contributing to the production of a substantial number of reportable objects.

Given the operational diversity of these reporting demands, the development of a single, representative use case was strategically prioritized for this MFW, enabling a focused and manageable implementation that could be executed effectively within the constraints of the available timeframe and resources. Although the update process for the selected report is relatively fast, the overall workflow remains largely manual – requiring daily extraction, screenshot capture, and email distribution –, thereby inhibiting interactivity and constraining the scope of insights, as the existing reports primarily focus on production data.

The following figure provides a visual representation of the current reporting workflow, emphasizing the sequential and manual steps involved from data extraction to final dissemination.

Figure 1 - Current Reporting Workflow.

3.3. Identified Challenges and Needs

Building upon this analysis, the research targets to examine the current reporting practices within the insurance company, identify key challenges and explore how BI can transform these processes through automation and interactivity.

This project was initiated to address three major operational challenges, to lead to enhancing workflow efficiency and effectiveness within the organisation:

1. **System Performance Optimization** – Concerns were raised by the IT department regarding frequent and excessive access to the Operating System, negatively impacting overall system performance. The project aims to reduce this dependency by providing alternative means of accessing necessary data.
2. **Improving Report Management Processes** – The current process for developing reports and dashboards is time-consuming, which limits the ability of report creators to focus on other critical tasks. The initiative seeks to restructure these processes, thereby reducing development time and increasing efficiency.
3. **Enhancing Report Readability and Engagement** – Reports were primarily in tabular form, thus enhancing their visual design is essential to make them more readable and easier to interpret. This project lines up with better extraction of insights by end-users.

The primary deliverable of this initiative is a roadmap for the implementation of BI-driven reports, meticulously developed based on end-user requirements and focused on highlighting key metrics essential for performance evaluation.

3.4. Selected Reporting Use Case

This study focuses on a specific and recurring reporting process involving the daily monitoring of product-level production volumes. Currently, this process is managed through two separate Excel files, each dedicated to one of the two product categories – savings and risk-related. These files contain pivot tables with separate sheets for products, as well as an aggregated overview, where the data is extracted directly from the operational system.

These reports – primarily used by senior administrators and board members – are extracted in response to high-priority information requests, which correspond to repeated manual updates, followed by the delivery of static screenshots from the pivot tables via email. The lack of automation and interactivity requires team members to spend considerable time maintaining and distributing the reports, often multiple times a day, besides their dependency on tacit knowledge. Furthermore, the static nature of the current reporting environment limits users' ability to explore different dimensions or levels of details in the data without new solicitations, which delays decision-making even further and places additional workload on the team.

3.5. Methodological Approach

The project follows a structured approach to ensure the solution effectively addressed business needs and met stakeholder expectations. The process began with a series of working sessions with the marketing and commercial teams – the primary creators and users of the existing reports – to understand the main performance indicators and their limitations. A key outcome of these conversations was the identification of the core KPIs, defining the scope of the dashboard. Once the goals and data needed were clear, the underlying data sources – that form the foundation of the dashboard's data model and its structure – were identified. Due to the absence of a centralized system, Microsoft Access was used as an intermediate layer to collect, clean and structure the raw data. The modelling phase was essential to prepare the data for Power BI and to make sure the metrics could be aggregated and filtered correctly. Furthermore, the initial part of the development process began with a draft version of the dashboard that was shared with the end users in informal sessions, where they gave feedback on the business logic behind the layout. To ensure that the collaborative feedback was continuous, this cycle was repeated several times, allowing for users to request adjustments to the visual hierarchy or filter options. Although the entire process was documented informally – with notes taken during each review session and changes tracked in working files – there were no formal usability tests.

4. STRUCTURE OF THE REPORTING SOLUTION

This section presents the structured of the reporting solution developed to support the automation of internal reporting processes through BI tools, within the context of a Portuguese life insurance company. It outlines the blueprint of the future reporting platform, illustrating how disparate data sources – both internal and external – will be unified, processed and delivered to end users via Power BI. The goal is to consolidate information from the selected existing reports into a centralized interactive dashboard, featuring two main views – financial and risk products –, while also allowing interactive product-level filtering and exploration. In addition to replicating the current information provided by the pivot tables, the redesigned report will also integrate claims-related data, to offer a more comprehensive view of operational performance, where the administrators can analyze the net daily production flow. The solution is expected to reduce the time spent updating reports, improve data quality -and empower users with self-service access to insights. Beyond addressing current inefficiencies, this development lays the groundwork for broader BI adoption across the organisation, ensuring that reporting evolves from static, manual documents to dynamic, data-driven decision support tools.

At a high level, the reporting solution – outlined in Figure 2 – is designed around four core components, which will be detailed in the following sub-sections of this chapter.

Figure 2 - Components of the Reporting Solution.

4.1. Architecture and Data Sources

This section outlines the layered architecture of the reporting solution, designed to streamline data integration and delivery. Raw data is processed through a structured ETL pipeline, with scheduled updates to maintain data freshness and consistency, before being ingested into Power BI and delivered as interactive dashboards to users. The modular design replaces a fragmented reporting process that replaces the previous reliance on static Excel files, PDFs and screenshots. By centralizing the data flow, the new architecture enhances automation, supports unified reporting, and scales to allow future integration of additional data sources.

The data sources for the general solution are both internal and external systems, including GIS (the operational platform), web-based data and inputs received via email. However, the source integrated into the solution only includes GIS system, from which production data is exported. The new approach automates this integration into Power BI and additionally incorporates claims data – also sourced from GIS – to calculate net production flow, a key metric previously unavailable in existing reports.

4.2. Tools and Technologies

The technological stack supporting the solution was carefully selected based on its ability to ensure seamless data integration, automation of manual processes, and compatibility with the organisation's existing infrastructure. The solution is implemented relying on a combination of tools – some already familiar and others newly adopted – that together support the architecture's system and enable scalable, self-service analytics.

Power BI was selected as the core BI platform for its intuitive interface, robust capabilities in structured data transformation, and support for dynamic, interactive dashboards with automated refresh schedules. To enable integration with the GIS system, Microsoft Access was used as an intermediary layer because of its compatibility and flexibility in handling structured data from legacy systems. This approach was an effective workaround given the absence of centralized data architecture such as a data hub or DL.

Through Access, raw operational data is retrieved, structured into intermediary tables, and prepared for further modelling. A batch (.bat) file is used to trigger an Access macro that automates the data extraction and preparation process. To ensure that the .bat file executions were scheduled without requiring manual intervention, the windows tool – Microsoft Task Scheduler – was employed to automate the periodic data extraction workflow. Its simplicity and easy integration with the rest of the system made it a practical solution for maintaining regular data updates under the existing infrastructure. Figure 3 contemplates the principal technologies used in the project, outlining their respective advantages and limitations.

Tool	Function	Advantages	Limitations
Microsoft Access	Data storage and structuring	- Easy integration with power BI - Suitable for transforming and cleaning datasets	- Not scalable - Limited concurrent access
Microsoft Power BI	Data visualization, dashboard creation, and distribution	- Real-time interactive dashboards, flexible design - User-friendly - Cloud-based solution	- Require licenses for better automation opportunities - Limited complex data preparation
Batch File (.bat)	Executes pre-defined operations (as Access macros)	- Lightweight and scriptable - Enables task automation without user interaction	- Requires command-line knowledge - Limited error reporting
Microsoft Task Scheduler	Scheduling of batch processes	- Built-in windows tool - Reliable for periodic tasks	- Limited interface - Less robust for complex workflows

Figure 3 - Summary of Tools used in the Solution.

Although recognized as a transitional solution, this approach provides a functional bridge between operational systems and the Power BI reporting layer. In line with the long-term strategy, this integration layer is expected to evolve into a more scalable and modern architecture that supports advanced data processing and real-time analytics. These technologies complement each other within the solution, forming a cohesive architecture: a layered and modular system designed to replace fragmented, manual reporting processes.

4.2.1. Power BI

Power BI is a powerful BI and data visualization tool developed by Microsoft. It was originally introduced in July 2011 under the name Project Crescent, being incorporated into Office 365 as Power BI two years later, culminating in its official public release in 2015 (Singh et al., 2023).

This Microsoft tool simplifies data analysis through intuitive visualization features, by converting complex datasets into compelling dashboards and reports, where visual elements play a crucial role in improving data comprehension and fostering actionable insights. The platform supports multiple data formats, such as Excel files, SQL Server datasets and CSV files, enabling users to create datasets directly from these sources and manipulate data with built-in features. A notable characteristic is related to the restructuring of data analysis workflows and improvement of efficiency, since the platform admits working across multiple sheets simultaneously and offers filtering functionalities to empower data exploration with automatic refreshes (Becker and Gould, 2019).

Power BI comprises three main components: Power BI Desktop, Power BI Service, and Mobile Apps. Power BI Desktop enables report designers to connect data sources, transform datasets using the Power Query Editor and build interactive reports. Once finalized, these reports can be published to the cloud through Power BI Service, which allows users to view, interact and personalize their dashboards without altering the original reports, supporting collaborative features. Meanwhile, the Mobile Apps extend access to real-time data, allowing users to interact with dashboards on mobile devices, reaching the content on-the-go (Altdorf, 2024).

Power BI is a data model-based tool that distinguishes itself from traditional spreadsheet-based tools like Excel. It allows the construction of reusable models, where data is logically structured with hierarchies and relationships between tables, minimizing the need for repetitive query writing (Allington, 2021). Power BI's data model supports the reusability and scalability of analytical models, supporting advanced features and encouraging the use of dimensional schemas such as the star schema, which provides an ideal logical structure for analytical performance (Russo and Ferrari, 2020).

In the world of data analysis, Power BI has facilitated the creation of interactive and detailed reports through impactful features like Data Analysis Expressions (DAX), which enable dynamic calculations. DAX is a formula language used to perform complex calculations within the data model, allowing for more advanced and interactive analysis. It is designed to support deep data exploration by altering filter contexts and building dynamic measures (Russo and Ferrari, 2020). Data modelling is crucial for the effective use of DAX, as it is necessary to define relationships, manage filter propagation and structure the data in a star schema. This language operates directly on tables and columns, allowing analysts to control the calculation context and perform aggregations across related tables. It is possible to compute advanced metrics without the need to add permanent columns to the dataset that would serve limited, formula-specific purposes. This functionality is critical for building dashboards with KPIs that adapt in real-time to user interactions, while simultaneously optimizing both model clarity and memory usage (Allington, 2021).

4.3. Dashboard Design Principles

This chapter presents the initial draft of the metrics contained on the dashboard. Rather than simply reproducing the static report, the dashboard structure was carefully reimagined to improve interpretability, relevance, and user interaction.

It is organized into two primary views – Financial Products and Risk Products – each divided into three key sections that exhibit the most strategically relevant performance indicators:

1. **Sales Production** – Displays current and historical production volumes. This allows users to identify trends, compare performance over time and monitor the evolution of new business.
2. **Claims** – Presents data on claim volumes and absolute counts, enabling users to assess the financial impact and risk exposure across different product lines.

3. **Net Production Flow –** Introduces a new metric by combining production and claims data to show the net business performance, filling a gap not addressed by previous reports.

The metrics are measured in monetary volume – for financial products – and in number of policies – for risk products –, reflecting the distinct nature of data and the analytical objectives associated with each domain. Assessing risk-related metrics by policy number allows the user to better analyze the exposure and dynamics of its portfolio.

The design of the dashboard and the selection of metrics were guided by the specific analytical needs of the marketing and commercial team. These business units provided KPIs and reporting priorities, which shaped both the structure of the data model and the visual layout of the dashboard.

To ensure analytical depth, each section incorporates drill-down functionality across multiple dimensions: commercial (business units, and categories), geographic (branch, country, and regions), channel (branch or digital), and different time levels (day, last month, last year and others). These dimensions offer flexibility, allowing the dashboard to serve both high-level strategic overviews and detailed operational analysis.

Design principles emphasize clarity, simplicity and accessibility: charts and KPIs are organized with logical grouping and consistent visual hierarchy; filters are intuitive and non-intrusive; and colour is used sparingly to draw attention to key variances. The dashboard was developed in Power BI Desktop, available on the company's shared drive, so that it can be automatically refreshed every day and be accessible to all users. Throughout the design process, feedback was continuously gathered from operational managers and board members via informal interviews. This iterative collaboration ensured that the final layout met real-world business needs while maintaining usability and interpretability for a wide range of users.

5. PROJECT DEVELOPMENT

This work is based on the implementation roadmap proposed by Vercellis (2009), adapted to the organisational context to support the practical application of BI processes and this project. After defining the architecture system and selecting the appropriate technologies, the next step was to implement the solution by translating the theoretical design into a functional system – handling data sources, developing the integration pipeline, and deploying the BI platform. This project was carried out individually as part of a MFW, in close collaboration with the department and internal shareholders. Although it did not follow a formal project management methodology, the execution was guided by an iterative and user-centered approach. This method allowed for continuous improvement based on user input, ensuring that the final solution was aligned with both functional needs and organisational constraints.

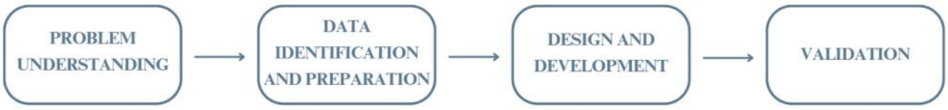

Figure 4 - BI Solution Development Process.

5.1. Problem Understanding

The first step in the implementation process was to gain a comprehensive understanding of the existing reporting environment, as outlined in the previous chapter and to engage directly with key stakeholders from both operational and managerial levels. To better understand the business context and user expectations, informal meetings and interviews were conducted with branch managers, operational staff and members of the executive board. The goal was to identify pain points and requirements right from those involved in producing and consuming the reports, ensuring that the most relevant metrics for decision-making are included, along with any features or functionalities absent in the current setup.

Several opportunities for improvement were identified throughout this stage, by addressing inefficiencies in the existing process. Report distribution will be centralized through shared dashboards, enhancing accessibility and consistency, as users can access from a unified data source instead of restricted file sharing. Analytical capabilities will be significantly improved via interactive dashboards with standardized filters and stakeholder reliance on specific individuals will be reduced through clearly documented and repeatable processes.

5.2. Data Identification and Preparation

The development of the reporting solution entailed the identification, extraction, and preparation of data, each characterized by distinct structural features and integration complexities. A crucial component of this phase involved consolidating the relevant datasets from the GIS System into a unified repository, gaining a thorough understanding of their characteristics, and designing appropriate transformation procedures to ensure consistency and analytical reliability.

To support this process, a Microsoft Access database was developed as a transitory yet centralized data management solution, where this environment enabled the structure execution of queries that facilitated the integration of data sources into a coherent system. The resulting data model encompasses four core datasets – including production and claims related to financial products, as well as policy issuance and cancellations for risk products. The primary tables are complemented by a set of auxiliary tables containing information on commercial structure hierarchies, product nomenclatures and temporal references, which provide necessary data for classification and normalization.

In terms of data preparation, several actions were undertaken to promote consistency and data integrity. Initially, the Access tables experienced data cleaning and standardization processes, including the resolution of formatting discrepancies and the harmonization of column names, data types and value mappings across datasets. To enable seamless integration with Power BI, the source tables were further transformed into a normalized schema. This included the enforcement of unique primary keys across tables, which is essential for establishing relational links within the data model and supporting robust analytical operations.

Once integrated into Power BI, the data model was constructed according to a star schema design, optimizing for performance, scalability, and analytical clarity. At the core of this architecture are four primary fact tables representing the core business processes: claims (Fact_Claims), receipts (Fact_Receipts), new policies (Fact_NewPolicies), and cancelled policies (Fact_CanceledPolicies). These are enriched through well-defined dimension tables such as product catalog (Dim_Products), organisation hierarchy (Dim_CommercialStructure), calendar (Dim_Date), payment frequency (Dim_Fracturation) and, for financial products, claim types (Dim_ClaimType), for risk products, cancellation reasons (Dim_CancellationReason). These relationships are defined through uniquely structured keys, enabling accurate filtering, aggregation and slicing across dimensions.

The construction of primary keys was a critical step in designing the relational schema of the database, as it guarantees the individuality of records and maintains referential integrity across tables. In the claims and receipts datasets, fields such as COD_SINISTRO and COD_RECIBO were already non-redundant codes with no duplicates in the original data, being adopted as primary keys themselves. However, for the remaining tables that did not include a pre-existing unique identifier, it was necessary to construct them by combining two fields – MOD and PROPOSTA –, thereby ensuring record-level uniqueness. These keys formed the foundation for defining one-to-many relationships between dimension and fact tables, ensuring that filtering behaviour in Power BI was both accurate and efficient.

In addition to the preprocessing steps within Microsoft Access, data cleaning and transformation procedures were performed in Power BI to refine the datasets for analysis, leveraging Power Query for advanced transformation logic. The first adjustment involved the composition of three separate columns into a [DATE] field through the fact tables, generated using the #date function within a custom column expression, ensuring compatibility with other temporal dimensions. Besides that, a standardization task was realized to remove components and enforce a uniform data format, enabling a consistent join with the calendar reference table. Regarding the product-related data, to connect the master product table with the remaining fact tables, it was necessary to create a derived field – product code within the company – by joining two pre-existing columns [MOD] and [VER] to match [MV]. However, to guarantee the correct key, [VER] was transformed by paddling single-digit values with a leading zero.

To ensure a clean and organized data model, two dedicated DAX measure tables were implemented: one for financial indicators (MEASURES_SAVINGS) and another for risk indicators (MEASURES_RISK). These tables exclusively store calculated measures – do not hold physical data – and therefore have no direct relationships with other tables. Instead, the DAX measures fields from already-related tables, leveraging the established relationships to compute values dynamically. The separation of analytical logic from physical data structures contributes to a clearer distinction between raw data and calculated KPIs, also becoming significantly easier to manage calculations, apply naming conventions and support scalable report evolution.

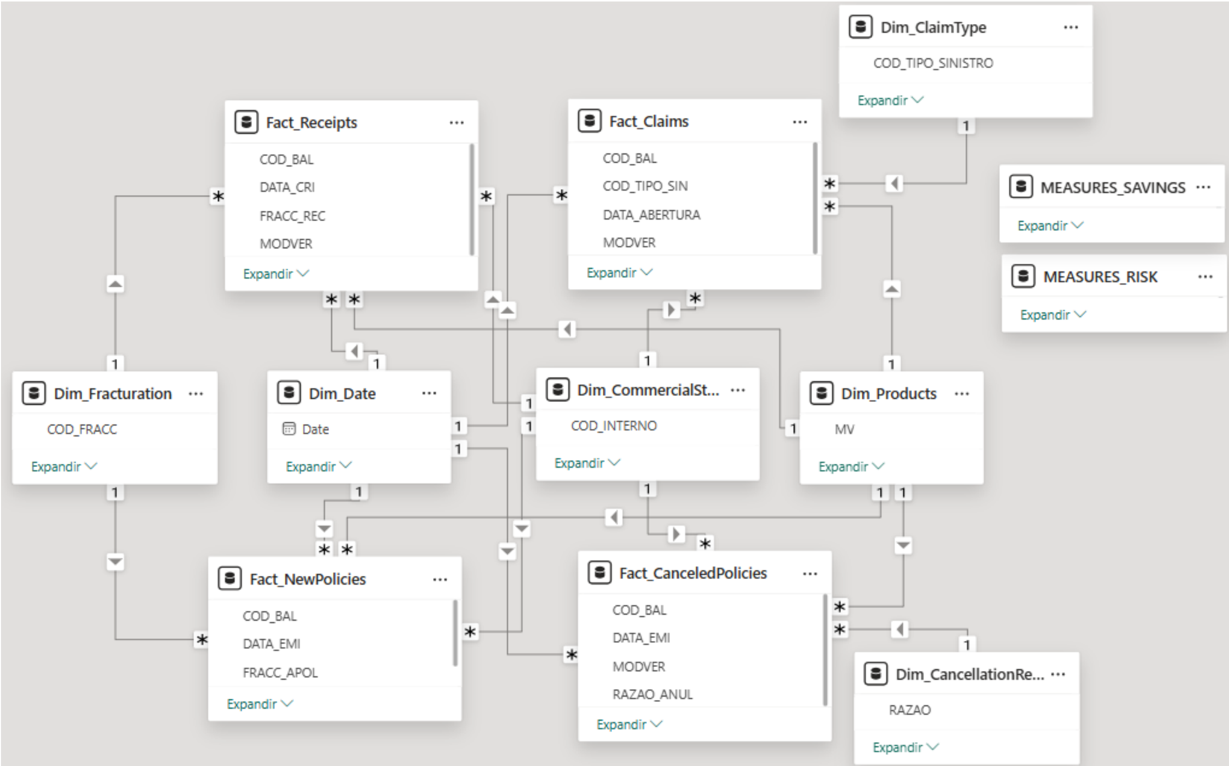

Figure 5 - Relational data model in Power BI.

5.3. Design and Development of the Solution

The system architecture previously defined guided the implementation of the reporting solution, while also adapting to technical constraints and system limitations encountered during the development phase. A primary challenge involved the integration with the GIS system, which serves as the main operational data source. Since the platform is not designed to handle concurrent access from external reporting tools, a workaround was implemented using a batch (.bat) file to trigger a Microsoft Access macro. In the context of large and complex datasets, to further enhance performance and stability, this macro connects to the GIS system, extracts the necessary data and executes queries into static physical tables at scheduled intervals. The static tables generated by Access macros are directly imported into Power BI, decoupling the preprocessing logic from the visualization layer. This strategy guarantees that data freshness is preserved without impacting the performance of the source system, by generating an intermediate dataset optimized for Power BI consumption. The integrated approach – combining Microsoft Access macros with the Windows Task Scheduler to execute batch files – not only allows an automated and reliable data extraction, but also contributes to minimize system load, optimize resource management and overall performance improvements.

This implementation strategy – recognized as a temporary solution – has proven effective in ensuring a high level of automation and data reliability, enabling the delivery of critical business insights trough tools such as Power BI, even within the constraints of the existing infrastructure. The long-term strategy involves migrating to a more modern and scalable architecture, that supports real-time data pipelines and centralized data storage. The reliance on intermediary tools will reduce and, therefore, this technological evolution fosters a more future-ready environment to meet the growing demands of data analysis in the sector.

Development Process

Complementing the data architecture and automation strategy, an iterative and user-centered approach was pursued to develop the dashboard with a strong technical focus on performance optimization, adjusted according to practical constraints and user feedback. The creation of the initial prototype was based on replicating the structure of existing static reports while introducing interactivity and filters, that allow the delivery of a scalable and intuitive reporting solution.

This first version confirmed the feasibility of connecting GIS data via Microsoft Access and served as a valuable prototype for presenting it to key stakeholders. This phase also involved structured testing sessions with operational managers and board members, who represent the primary audience of the reporting tool. Feedback was gathered through informal interviews and direct observations, confirming the overall usefulness and usability of the solution, while also highlighting specific areas for refinement.

The following enhancements were identified as high-priority changes:

- Implementing consistent visual hierarchy.
- Expanding filtering capabilities across dimensions.

- Adding tendency indicators (up and down arrows) to KPI cards to visually indicate performance direction.
- Creating a dedicated slot to track the production of the newly launched product.
- Developing a mobile-optimized version of the dashboard to ensure accessibility across devices.

These technical and functional adjustments resulted in a solution that aligns user expectations and operational requirements with fully automated data updates and integrated KPIs.

5.4. Final Dashboard Overview

The dashboard is organized into two main analytical perspectives – Financial Products and Risk Products – which users can easily access through dedicated navigation tabs at the top of the interface, promoting intuitive analysis. Each view contains KPI cards, bar and pie charts, and dynamic filtering tools, granting high-level monitoring and granular data-driven exploration simultaneously, depending on the user's needs. The clear and uniform layout across both tabs ensures visual usability, with each view consistent structured into three key sections – Production, Claims and Net Flow – which collectively offer a complete overview of operational performance.

In the upper left section, KPI cards display the most relevant indicators for the year-to-date (YTD) and the current month of 2025. To improve interpretation, the visual hierarchy was refined using trend icons (up and down arrows) placed directly in the cards, making it easier to compare the evolution relative to the previous period. In the Financial view, the dashboard provides immediate visibility into accumulated production and claims for the year, the trend in net flow (comparing the current and previous year), production and claims variations (with real-time comparisons to the previous month), and the financial net flow for the current month. The arrows in the cards allow users to quickly assess business results by visually communicate positive or negative performance changes without the need to interpret the numbers. Similarly, in the Risk view, the focus is on the number of new policies issued and the number of cancelled policies for 2025, the variation in the annual net flow, the trend on new and cancelled policies of the month (also with real-time comparisons to the previous month), and the risk net flow for the current month. These values are supported through trend arrows, maintaining consistency with the previous view and supporting a quick understanding of key shifts in portfolio movements. Alongside the static indicators, the dashboards include several interactive data visualizations that decompose the metrics by relevant dimensions, offering deeper insights into how different areas contribute to the overall performance. In both views, a line chart is used to display the daily trends of production, claims and policy issuance throughout the current month. This temporal breakdown allows users to detect peak activity days or anomalies. Adjacent bar charts extend this analysis to a monthly aggregation level, showing the progression of production and claims over the year. Complementing the temporal charts, pie charts are used to break down production and claims by key dimensions. In the Financial view, claims are segmented by type and, similarly, the Risk view has categorized the reasons for policy cancellations. Production is categorized by payment frequency in both dashboard perspectives offering consistent insights into how clients prefer to structure their payments. This level of segmentation provides actionable insights into client behaviour and product sustainability. At the bottom of each dashboard, ranking visuals present *Top 5* breakdowns – departments and products – by sales and number of new policies, which can help in aligning marketing strategies or understanding where the company is underperforming.

A dedicated section was incorporated into the Financial view to highlight the performance of a newly launched product. This slot was created to encounter a specific need identified during stakeholder interviews: the ability to monitor the new offer without relying on separate reports. Visually aligned with the rest of the dashboard, this section includes KPI cards for overall and YTD production, as well as a supporting bar chart detailing its monthly contribution. It allows users to isolate and track the product's success independently from the broader portfolio. Given that it was the only product launched during the period analysed, this feature was not replicated in the Risk view.

Regarding usability, the integration of a dedicated filter panel significantly enhances the dashboard's interactivity and analytical flexibility. This panel supports cross-sectional analysis by segmenting data across multiple dimensions, including department, product group and channel. The interface promotes the user's independence by dynamically updating all visuals based on the filters, making Power BI's interactivity especially valuable for intuitive data exploration and deeper insights.

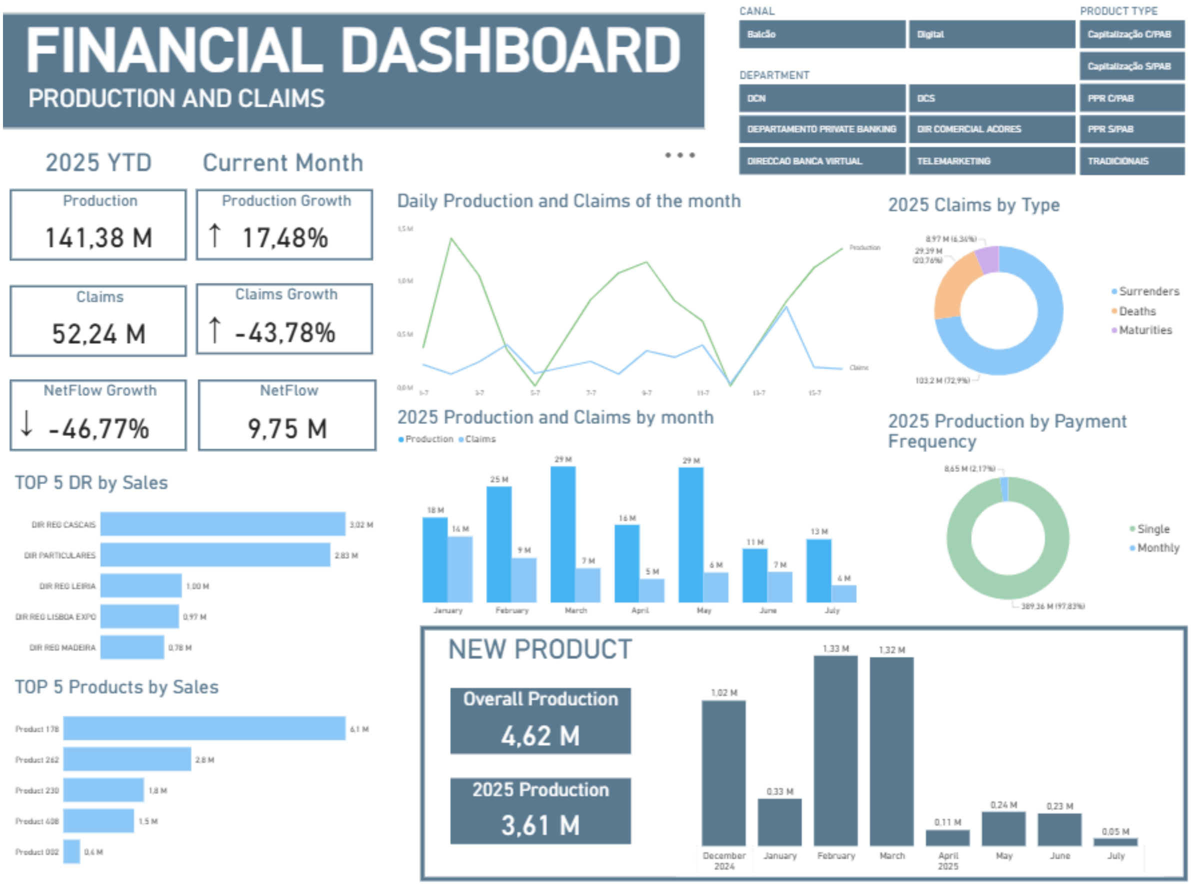

Figure 6 - Financial Dashboard.

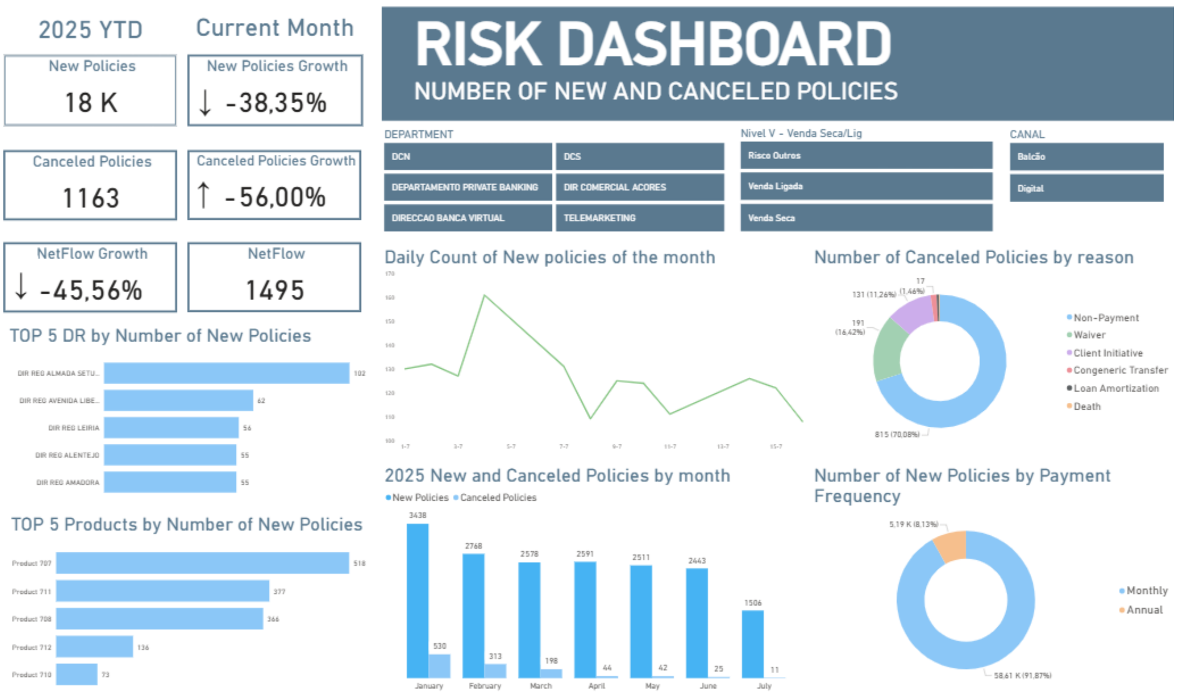

Figure 7 - Risk Dashboard.

To ensure broader adoption, a mobile-optimized version of the dashboard was also developed using Power BI's mobile layout view, preserving the core visualizations while reorganizing content to fit smaller screens – optimizing both readability and user navigation. The mobile dashboard for financial and risk products highlights KPIs through cards regarding YTD and monthly performance. The financial dashboard includes the new product area and, in the same way, its mobile version also features this section. This adaptation supports remote access and informed decisions on the go.

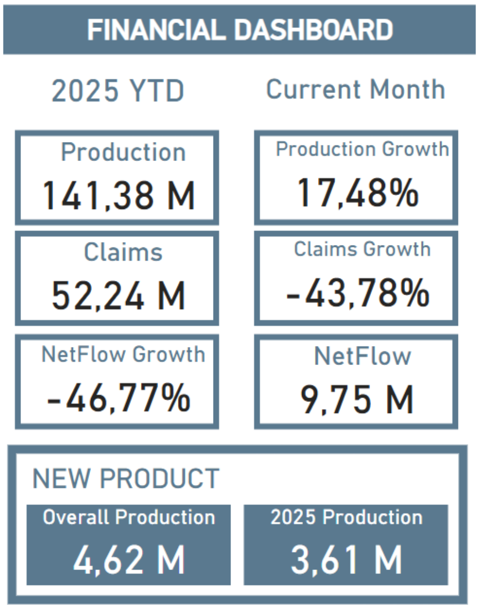

Figure 8 - Financial Dashboard – mobile layout.

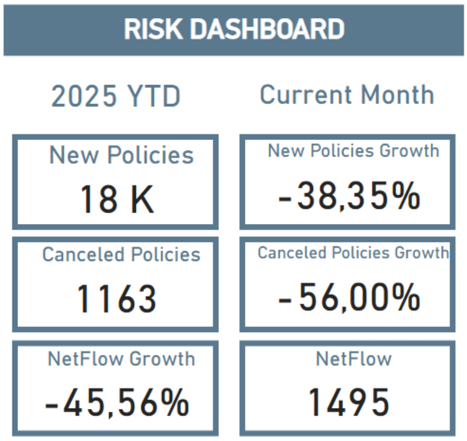

Figure 9 - Risk Dashboard – mobile layout.

The report is published in a shared company directory and benefits from a fully automated daily refresh, due to a streamlined workflow, ensuring up-to-date information with minimal effort. Overall, the final dashboard is a representation of the business and the realization of the solution’s goals – automating delivery, accessible data and user-friendly.

5.5. Impact on Efficiency and Decision-Making

The implementation of the automated reporting solution had a positive impact on operational efficiency by shifting the way users interact with data. The project replaces a fragmented, manual workflow with a more fluid, self-service experience built on Power BI, achieving measurable improvements in productivity, data accessibility and velocity of getting business insights.

Although not formally measured, this change had a clear impact on reducing both the time required and the workload on the reporting team. It enables analysts to redirect their focus towards more strategic tasks – for example, performance monitoring and ad hoc analysis – while also improving responsiveness across departments. In parallel, the solution reduced dependency on specific individuals who previously held critical knowledge about report logic.

From a decision-making standpoint, the dashboard has proven to be a practical tool for decision-making, since this self-service approach shortens decision cycles, empowering managers to take on a more analytical role. Additionally, the introduction of net production flow as a metric enabled a more accurate evaluation of business performance, effectively closing a gap that existed in former reports.

Feedback from stakeholders confirmed a high level of satisfaction, particularly regarding ease of use and the value of having a mobile-optimized version of the dashboard. It was also reported that the dashboard has been increasingly used in operational meetings and performance reviews. While these impacts are qualitative, the solution represents an important toward fostering a broader data-driven within the organisation, with the aim of making decisions increasingly guided by data.

6. CONCLUSIONS

This project started to optimize the reporting process within a Portuguese life insurance company by designing and implementing an automated solution using Power BI. The initiative successfully transformed a previously manual, fragmented workflow into a centralized and dynamic report capable of empowering data-driven decision-making. The fulfilled dashboard addressed three core operational challenges: improving system performance, reducing the reliance on manual tasks and making business data more interpretable.

Furthermore, beyond the technical achievements, the project also contributed to promote knowledge sharing and reducing dependency on individual expertise. Business logic passed informally between team members is now fully embedded in the Power BI data model, more precisely through DAX, ensuring transparency, consistency and easier maintenance. This shift supports the development of a more collaborative data culture across the organisation.

While the implemented solution marks a significant improvement over the previous manual reporting procedure, several limitations were identified throughout the project and should be considered as the solution evolve.

- **Transitional Architecture** – The reliance on Microsoft Access as an intermediary data processing layer was a practical and cost-effective decision given the absence of a centralized data platform at the time of implementation. Yet it is not ideal for long-term scalability or real-time data.

- **Data Source Scope –** Due to time constraints, and to simplify, the initial prototype focuses exclusively on data derived from GIS system. However, other relevant sources are not yet integrated, limiting the range of available insights.
- **Manual Data Standardization –** Some preprocessing steps, including format standardization and key creation, require manual intervention due to inconsistencies in the source system. Although mitigated through Power Query and DAX, these operations limit full automation.
- **Limited Quantitative Indicators of Adoption –** The project did not include a formal measurement of user engagement, so it is difficult to quantify adoption rates, frequency of use or decision latency – metrics that would help strengthen the case for future BI investments. Regarding mobile testing, it was limited to a small group of users, meaning that broader validation is necessary to ensure usability across devices and screen sizes.

These limitations reflect the project's current maturity stage and are already being considered in the roadmap for future developments.

To build on the momentum of this project and expand its benefits across the organisation, several avenues for future work have been recommended. The long-term vision involves migrating to a modern data architecture, replacing the Microsoft Access intermediary layer with a cloud-based DW that would support real-time integration and long-term scalability. Another important step involves expanding the range of data sources integrated into the solution, incorporating CRM data, external market feeds, among others, would enrich the analytical context. Additionally, the approach implemented on the dashboard can serve as a reference for reporting practices organisation-wide, with the potential to expand the framework developed in this project across other departments – helping them define their own KPI and adopt similar strategies adapted to their operational realities. Lastly, with technological evolution, the introduction of advanced analytics and predictive functionalities is a natural next step, by leveraging AI features or connecting to external machine learning platforms that allow forecasting and behavioural analysis.

While the outcomes of the project were generally positive, the process revealed important trade-offs between speed of delivery and technical robustness. The decision to prioritize immediate impact using existing tools over investing time in a more scalable infrastructure reflects a realistic approach for the year's pipeline. Similarly, the focus on a single data source allowed for quicker prototyping and validation, although the limited analytical scope and cross-functional relevance of the initial dashboard. These choices were necessary to deliver value quickly, but they also emphasized the need for a more scalable and integrated foundation moving forward. Moreover, the project highlighted the critical importance of cross-team collaboration – not only in the technical sense, but also in ensuring knowledge continuity and fostering ownership among end users. These soft dimensions proved as crucial as the technical implementation itself in driving adoption and setting the stage for long-term transformation with the organisation's growth.

In conclusion, this project not only delivered an automated reporting tool, but also introduced a new mindset in the company, that helped to shift the organisation closer to a culture where decisions are grounded in data with a more solid foundation.

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