Lisbon School of Economics & Management
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MASTER

MANAGEMENT INFORMATION SYSTEMS

MASTER´S FINAL WORK

INTERNSHIP REPORT

DATA ANALYSIS AND AI USAGE FOR CUSTOMER SUPPORT IN THE PORTUGUESE ACQUIRING SECTOR

ANTONIO VASCO QUEIMADO MURTEIRA

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GLOSSARY

AI - Artificial Intelligence

BI - Business Intelligence

CAPEX - Capital Expenditure

DAX - Data Analysis Expressions

ETL - Extract, Transform, Load

HUE - Hadoop User Experience

IT - Information Technology

KPI - Key Performance Indicator

LLM - Large Language Model

M365 - Microsoft 365

ML - Machine Learning

NLP - Natural Language Processing

OPEX - Operational Expenditure

POS - Point of Sale

SAS - Statistical Analysis System

SAS EG - SAS Enterprise Guide

SQL - Structured Query Language

TSID - Tecnologias, Sistemas de Informação e Digital

UX/UI - User Experience and User Interface

ABSTRACT

This internship report describes the activities carried out at UNICRE conducted in the areas of Data & Digital Services and later Digital Experience & AI. The internship focused on the practical application of data analytics, business intelligence, and artificial intelligence to support decision-making and improve operational processes in the Portuguese acquiring sector.

The main activities involved developing SQL queries and data extraction processes, creating and enhancing Power BI dashboards, and testing and evaluating AI-based solutions.

Several dashboards were developed and improved to support different organizational areas, including IT operations, budget monitoring, and commercial performance analysis. These solutions contributed to the automation of reporting processes, improved data accessibility, and facilitated the monitoring of key performance indicators.

The AI initiatives that were developed, particularly the validation of conversational chatbots designed to support employees and customer service teams, were evaluated through structured testing and benchmarking. This process identified limitations and opportunities for improvement, contributing to the reliability and effectiveness of the solutions under development.

Overall, the internship demonstrated the value of Business Intelligence and Artificial Intelligence in transforming organizational data into actionable information. The experience reinforced the importance of data quality, clear visualization, and AI-assisted decision-making are in enhancing operational efficiency and advancing digital transformation efforts.

Keywords: Business Intelligence; Artificial Intelligence; Power BI; Data Analytics; Decision Support; Customer Service Automation

TABLE OF CONTENTS

Table of Figures

List of Tables

Acknowledgments

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1. INTRODUCTION

This report details the internship at UNICRE, a Portuguese financial company in the payments and acquiring industry. Part of the Master’s in Management Information Systems at ISEG, the internship provided an opportunity to apply and consolidate knowledge acquired throughout the master's program in a real-world setting and involved projects focused on AI, business intelligence, data analytics, and decision support.

The internship took place between November 2025 and May 2026, and the activities included developing SQL queries, extracting and preparing data from internal systems, validating datasets used in reporting, testing features under development, and creating interactive dashboards and reports using Microsoft Power BI. These activities improved the accessibility, quality, and usability of information while supporting operational and strategic decision-making processes. The internship also involved research on artificial intelligence, including analyzing market trends and testing two conversational chatbots: one designed to support customer service processes within the acquiring business and another to support UNICRE’s collaborators.

Founded in 1974, UNICRE is one of the leading Portuguese companies in the payment services industry. Through its acquiring and payment solutions with the REDUNIQ network, the company supports merchants and financial institutions across a wide range of payment operations. Given the importance of data in financial services, the organization provided a setting that supports the practical application of business intelligence methodologies and data analytics techniques in real-world business contexts.

This report describes the activities undertaken during the internship and analyses their contributions to both organizational objectives and professional development. In addition to presenting the projects undertaken and the technologies used, the report discusses the results achieved and reflects on the knowledge and competencies developed during the internship.

Artificial intelligence tools were used to assist with the preparation of this report, namely Claude, ChatGPT, Grammarly, NotebookLM, and ResearchRabbit. These tools assisted activities such as literature research, writing support, and language revision.

2. LITERATURE REVIEW

2.1 Business Intelligence core concepts and evolution

Business Intelligence (BI) is generally understood as the set of concepts, processes, and technologies that transform raw data into meaningful information to support decision-making (Watson, 2009; Chen et al., 2012). Beyond dashboards and reports, BI denotes the broader organizational capability to gather, organize, analyze, and disseminate information to improve managerial judgment and performance (Eboigbe et al., 2023). The literature typically differentiates among data, processed information, and actionable knowledge, highlighting that BI's value lies not in collecting data but in structuring it to inform decision-making. (Chen et al., 2012).

Although associated with modern platforms, BI is usually presented as an evolution of earlier traditions such as decision support systems, executive information systems, and data warehousing, rather than a new concept (Watson, 2009). More recent work places BI within a wider analytics landscape that integrates large-scale data, self-service analysis, and increasingly descriptive, predictive, and prescriptive techniques supported by machine learning and artificial intelligence (Chen et al., 2012; Eboigbe et al., 2023; Wissuchek & Zschech, 2025). BI can thus be read as a shift from relatively isolated reporting systems toward integrated analytical ecosystems capable of supporting both retrospective analysis and forward-looking action (Chen et al., 2012; Wissuchek & Zschech, 2025).

2.2 BI Architecture and Decision Support

Although BI architectures vary across organizations, there is a broadly consistent structure: data sources, extraction and integration processes, an analytical repository, such as a data warehouse, and user-facing tools for querying, reporting, and visualization (Dinesh & Gayathri Devi, 2024). The purpose of this architecture is not merely to store data; it is to distinguish analytical uses from operational transaction processing, incorporate diverse sources, and maintain historical data as a reliable foundation for analysis (Dinesh & Gayathri Devi, 2024; Chen et al., 2012).

BI's value lies in decision support across strategic, tactical, and operational levels. From market analysis and resource allocation to key performance indicator monitoring and faster response to process deviations (Chen et al., 2012). Empirical work shows that stronger analytics capability translates into competitive performance, an effect mediated by the dynamic and operational capabilities it enables (Mikalef et al., 2020). BI does not, however, replace managerial judgment: its success depends on capabilities suited to the organization's decision environment and on organizational and cultural readiness rather than on technology alone (Işik et al., 2013; Mikalef et al., 2020). For this reason, contemporary work increasingly frames BI as an organizational capability in which information is systematically exploited to improve outcomes (Adewusi et al., 2024).

2.3 BI benefits, Organizational Impact and Challenges

The benefits attributed to BI tend to converge on a few dimensions: improved informational visibility through the consolidation of dispersed data, faster identification of trends and deviations, and stronger coordination through shared metrics across departments (Popovič et al., 2012). Applications are found in finance, operations, marketing, customer management, and risk monitoring, and the integration of BI with big data analytics has widened this range further (Chen et al., 2012). The incorporation of artificial intelligence has further extended BI toward predictive modeling and more automated decision support (Eboigbe et al., 2023). At a strategic level, BI has been linked to the capacity to sense threats, synthesize information, and adapt decisions accordingly (Malawani et al., 2025; Mikalef et al., 2020). Popovič et al. (2012) relate such effects to organizational maturity and information culture, suggesting they are cumulative but never automatic.

Despite this potential, adoption is consistently described as challenging. A persistent barrier is data quality: incomplete, inconsistent, or poorly defined source data undermine user trust and produce misleading outputs regardless of front-end quality (Işik et al., 2013). Integration and governance constitute a second challenge, as BI must reconcile heterogeneous operational systems while also addressing data security and a shortage of skilled professionals (Adewusi et al., 2024). Sustained user engagement, training, and executive support are equally decisive; without them, even technically robust solutions may remain underused (Popovič et al., 2012).

2.4 Data querying and data quality

If BI is the visible analytical layer, data querying and preparation form the infrastructure that makes it possible. Querying operationalizes information needs: in relational environments, SQL allows analysts to filter, join, and aggregate data, translating business questions into logical conditions, metrics, and data relationships (Chen et al., 2012; Adewusi et al., 2024). Well-designed queries enable precise, reproducible analysis and serve as an initial validation mechanism to detect gaps, duplication, and inconsistencies, whereas poorly designed ones may introduce distortions before reporting even begins.

The usefulness of analytical outputs depends directly on the quality of the underlying data, widely understood as "fitness for use" and treated as a multidimensional construct rather than a single technical attribute (Priestley et al., 2023). The dimensions most relevant in a BI context are accuracy, completeness, consistency, timeliness, and validity, which directly affect extraction, modeling, and interpretation (Pipino et al., 2002; Priestley et al., 2023). Because BI integrates multiple sources, quality problems rarely amount to simple entry errors; they often involve conflicting definitions, incompatible formats, or duplicated entities, so sustaining quality requires explicit measurement and continuous monitoring rather than one-off checks (Ehrlinger & Wöß, 2022).

2.5 Data Extraction, Preparation, ETL, and Cleaning

Data extraction and preparation are the stages through which operational data become analytically usable. In BI environments, this is typically formalized as ETL (Extract, Transform, Load), which remains a foundational mechanism for building analytical repositories (Dinesh & Gayathri Devi, 2024). The extraction phase identifies the relevant sources, fields, and time intervals; the transformation phase applies business rules and technical conversions; and the loading phase loads the results into a destination structure, such as a staging area or data warehouse (Dinesh & Gayathri Devi, 2024).

ETL is consistently described as one of the most demanding parts of BI projects, since it largely determines whether the resulting environment will be trustworthy and reusable (Dinesh & Gayathri Devi, 2024). Integration is inseparable from it: organizations operate through multiple systems built at different times and for different purposes, and reconciling their structural, semantic, and temporal differences remains a persistent challenge (Rahm & Do, 2000). Without integrated foundations, departments may report on the same business reality using inconsistent definitions, filters, or extraction criteria (Rahm & Do, 2000).

2.6 Relation between Data and Business Intelligence

These activities are decisive rather than peripheral for BI success. Kasten (2020) argues that decision-makers trust in analytics tools is essential because it affects both their adoption and the value organizations can obtain from them. Strong data governance and quality processes improve data quality management and enable more accurate analytics, whereas without these controls organizations are more likely to make decisions based on inadequate or inaccurate data (Miguel et al., 2024).

2.7 AI Chatbots and Conversational AI

Chatbots, also known as conversational agents, are software systems designed to interact with users in natural language, typically via text or voice. Driven by developments in natural language processing (NLP) and machine learning (ML), they have evolved from simple scripted assistants into sophisticated AI-powered systems capable of managing complex, contextual conversations (Adamopoulou & Moussiades, 2020). Their adoption has grown substantially over the past decade, particularly in customer service settings, where organizations use them to respond to queries, resolve issues, and interact with clients at scale (Nicolescu & Tudorache, 2022).

Rule-based chatbots operate on predefined decision trees or pattern-matching rules, producing fixed responses to recognized inputs. They are straightforward to implement and audit, but their rigid structure limits them to a narrow range of interactions and makes them poorly suited to handling unexpected variations in user language (Adamopoulou & Moussiades, 2020). Retrieval-based systems go a step further by selecting responses from a predefined repository using ML and NLP techniques to match user input to the most relevant candidate. These systems are more flexible than purely rule-based approaches but are still bounded by the quality and coverage of their response database (Pandey & Sharma, 2023).

Generative chatbots, by contrast, produce responses dynamically using language models trained on large amounts of text. The advent of transformer-based architectures and large language models (LLMs) has dramatically expanded the capabilities of this category, enabling systems to generate contextually coherent, open-domain responses on topics they have not explicitly been programmed for (Adamopoulou & Moussiades, 2020).

2.8 Automation and Efficiency Gains

One of the primary drivers behind chatbot adoption is the potential for operational efficiency. By automating the handling of routine and repetitive queries, organizations can significantly reduce the workload on human agents, lower response times, and cut operational costs (Adam et al., 2021). Unlike human operators, chatbots are available around the clock, can handle multiple conversations simultaneously, and maintain consistent response quality regardless of volume (Nicolescu & Tudorache, 2022).

In a study set within an e-commerce environment, Adam et al. (2021) showed that AI-powered chatbots offer operational cost savings and also shape customer behavior through social cues integrated into their design. Features such as assigning chatbots a name, a conversational style, or a human-like avatar increase the likelihood that users will comply with requests, such as providing feedback. This suggests that automation can improve efficiency without compromising the quality of engagement (Adam et al., 2021).

2.9 User Experience

While efficiency is a measurable benefit, the quality of the user experience ultimately determines whether a chatbot deployment succeeds. Følstad and Skjuve (2019) conducted an interview-based study with 24 users of customer service chatbots and found that the most decisive factor in user satisfaction was their ability to efficiently and adequately handle their inquiries. Users primarily engage with chatbots for productivity, seeking fast and accurate responses to requests, and quickly disengage when the system fails to meet those expectations.

Personalization plays an increasingly important role in this regard. Nicolescu and Tudorache (2022) identified, through a systematic review of empirical studies, that response relevance and effective problem resolution are the most influential determinants of positive customer experience with service chatbots. Personalization extends beyond addressing a customer by name; it encompasses the system's ability to adapt its responses to the user's intent, context, and prior interaction history. When chatbots demonstrate this contextual awareness, user satisfaction and the likelihood of continued use both increase substantially (Nicolescu & Tudorache, 2022).

Responsiveness is closely linked to user experience. Delays or failures in understanding user input generate frustration and undermine confidence in the system. As Følstad and Skjuve (2019) observed, users form their perceptions of a chatbot very quickly, often within the first few exchanges, which means that initial performance has a disproportionate impact on the overall experience.

The ability to transfer users to a human agent when the chatbot cannot adequately resolve a query is an often-underestimated evaluation criterion. Følstad and Skjuve (2019) found that users are more forgiving of chatbot limitations when a clear and accessible escalation pathway is available. Conversely, the absence of such a mechanism is a leading driver of user abandonment and negative experience.

2.10 Testing

Before deployment, chatbots must undergo thorough testing to ensure they perform reliably across a diverse range of inputs. Testing a conversational AI system presents distinct challenges compared to conventional software testing, because the space of possible user inputs is effectively unbounded and the quality of a response cannot always be assessed through simple true/false criteria (Li et al., 2022, as cited in Gao et al., 2022).

More recent evaluation approaches combine automated metrics with human evaluation panels, which assess dimensions such as coherence, intent alignment, and conversational naturalness. For task-based chatbots, including those deployed in customer service, functional testing is additionally required, covering intent recognition accuracy, entity extraction, and end-to-end task completion rates (Li et al., 2022, as cited in Gao et al., 2022).

2.11 AI chatbots Risks and Limitations

Despite their advantages, AI chatbots carry significant risks that organizations must manage carefully. One of the most discussed concerns in recent literature is the phenomenon of hallucination, which refers to the tendency of AI language models to generate responses that are fluent and plausible in form but factually incorrect or unsupported (Ji et al., 2023).

Privacy and data security represent another critical risk. Customer interactions with chatbots often involve sensitive personal or financial information, and the collection, processing, and storage of this data introduce significant compliance obligations (Adam et al., 2021). Organizations deploying conversational AI must therefore implement robust data governance measures alongside the technical solution itself (Adam et al., 2021).

From an organizational standpoint, successful chatbot deployment requires cross-functional coordination between IT, customer service, legal, and compliance teams. Defining the scope of the chatbot's competence, what it should handle, what it should refuse, and when it should escalate demands a level of deliberation that is frequently underestimated at the outset of a project. Furthermore, introducing a chatbot into an existing service workflow requires change in management efforts: both customers and frontline employees need to understand how the system works and its role within the broader service model (Nicolescu & Tudorache, 2022).

3. INTERNSHIP DESCRIPTION

This chapter begins with a brief overview of the host organization and then describes the department and teams where the internship was conducted. It aims to provide the institutional and operational context that framed the work carried out throughout the internship, as well as the tools used.

3.1 Unicre Overview

UNICRE is a Portuguese financial institution founded in April 1974, specializing in payment solutions and credit activities. Over the years, the company has played an important role in the modernization of payment methods in Portugal, particularly through its technological focus and its long-standing presence in the national market.

In the past, UNICRE operated through two main commercial brands. UNIBANCO was the first brand of UNICRE, associated with credit cards and later other financial solutions, including prepaid cards, meal cards, personal credit, and consolidated credit, while the REDUNIQ brand started in 1986, being the first brand in Portugal that was focused on payment acceptance solutions for physical stores and later online channels (UNICRE, 2025).

Although UNICRE's historical identity was closely linked to both UNIBANCO and REDUNIQ, this structure changed during the period covered by this report. On the first of March 2026, Novobanco, one of UNICRE's largest shareholders, completed the acquisition of the UNIBANCO business, meaning that from that point onward, REDUNIQ is UNICRE’s only brand. This sale is important to mention because it caused structural shifts and changes across the company, affecting most of it. Currently, the institutional presentation of UNICRE emphasizes REDUNIQ as the brand it holds, reflecting the company’s new organizational reality and focus following that transition.

Within the Portuguese market, REDUNIQ holds a particularly significant position due to its long history. As the market becomes increasingly competitive, REDUNIQ is pushed to innovate to stay ahead as the national leader in payment acceptance. This market relevance is visible in the company’s 2025 annual report, which states that REDUNIQ maintained leadership in the national payments market and processed 27.9 billion euros in transactions, corresponding to more than 890 million payment operations during the year (UNICRE, 2026). These factors help explain why UNICRE constitutes an important case in the Portuguese financial and payments sector, it’s a long-established institution and also one that remains strongly connected to digital transformation, innovation, and the evolution of electronic payments.

3.2 Departments and Divisions

TSID

The internship took place within TSID. This was the organizational area responsible for technology, information systems, and digital initiatives inside the company. TSID worked closely with several different internal areas and played a crucial role in supporting both operational needs, such as support, as well as ongoing digital solutions related to Acquiring.

Data and Digital Services

At the beginning of the internship, I was integrated into the Data & Digital Services department. This team had a broader structure and operated in a dynamic environment where communication with different profiles and functions was frequent. Due to the team's large size, most collaborators had different tasks, but the team’s main objective is to ensure the quality, consistency, and availability of data across the organization, enabling reliable decision-making and supporting business operations. Every morning at 9:35 a.m., the team held a daily meeting to align tasks, share progress, and discuss obstacles or ongoing issues. These meetings were useful not only for operational follow-up when necessary, but also for understanding the broader context of the projects in progress and how each person’s work connected with the team’s overall objectives.

Digital Experience and AI

Following the restructuring associated with the company’s new phase after UNICRE’s sale, I was placed in the newly created Digital Experience and AI department. Even though this represented a departmental change on paper, the core of the internship responsibilities did not change significantly. From the beginning, I had been working with Power BI and AI-related initiatives, so the transition was more evident in the organizational setting than in the actual tasks performed.

Still, there were some relevant differences between the two teams. In the second team, there was a stronger focus on learning more about AI and on exploring how AI could be used more directly in ongoing work. In addition, the new team was much smaller, and my supervisor was also now my team coordinator, which facilitated tasks. This smaller scale made communication more immediate and efficient, and the daily meetings also became quicker and more focused.

3.3 Methodology, Tools and Software Used

The work model remained hybrid throughout the internship. In general, there were two on-site days at the office each week, and one of them was always Tuesday, when the whole team would usually be present. This hybrid model created a balance between autonomy and collaboration. Overall, this organizational context contributed positively to the internship experience by combining technical learning, collaborative work, and exposure to a company undergoing relevant internal change at both the business and departmental levels.

Most of the collaborative tools used were part of the M365 ecosystem. The most frequently used tools included Microsoft Excel for testing, Microsoft Teams for efficient communication and remote meetings, SharePoint, where most testing documents were stored, Power BI for creating dashboards, Forms for creating forms, and PowerPoint for presentations. Outlook was also used for communication between teams and departments. Additionally, the software SAS Enterprise Guide and HUE were used for data querying and extraction. Supervision throughout the internship was ongoing, with the supervisor providing guidance, clarifications, and suggestions for improvement.

4. INTERNSHIP EXPERIENCE

4.1 Objectives of the Internship

Before the internship began, the work plan established a set of objectives that combined technical learning with organizational integration. At a general level, the internship was intended to provide practical exposure to ongoing Generative AI initiatives and, at the same time, to allow the development of skills relevant in an Information Systems context. The main objectives defined before the beginning of the internship were the following:

A) Support the execution and monitoring of Generative AI (GenAI) projects

B) Develop practical skills in testing, evaluating, and validating GenAI solutions

C) Gain understanding of project management and technical coordination processes within GenAI initiatives

D) Collaborate with the Marketing team to enhance the UX/UI design of GenAI chatbots and create initiatives to promote chatbot adoption

E) Contribute to the development and maintenance of chatbot knowledge bases

Taken together, these activities reflected an internship plan with both technical and organizational components. On the one hand, they involved direct contact with chatbot testing, knowledge bases, and dashboard development. On the other hand, they also required coordination with different teams, documentation of results, and attention to user adoption, which made the internship relevant not only from a technological perspective but also from a management and information systems perspective.

In that sense, the internship was well aligned with the broader orientation of the Master's in Management Information Systems at ISEG. The Master's brings together the technological and business dimensions of organizations, with a strong professional orientation and a focus on information systems planning, implementation, integration, and management.

4.2 Internship Chronogram

Table 1: Activity Chronogram prepared by UNICRE in November 2025

	Scheduling (months)					
Support project management activities (tracking milestones, deliverables)	X	X	X	X	X	X
Participate in coordination meetings (Data, IT, Marketing, Customer Service)	X	X	X	X	X	X
Contribute to the setup and configuration of GenAI environments and chatbot platforms	X	X				
Execute functional and user experience (UX) testing of GenAI chatbots		X	X	X		
Record and organize test results, identifying potential issues and areas for improvement	X	X	X			
Help maintain and update chatbot knowledge bases				X	X	X
Collect feedback from users to improve chatbot usability and responses			X	X	X	X
Participate in brainstorming and review sessions for new GenAI use cases			X	X	X	X
Build Power BI dashboards to monitor chatbot response quality	X	X				

The internship took place from 24 November 2025 to 23 May 2026 and was organized through a monthly activity diagram that distributed the main tasks across the internship period.

Even though the chronogram provided a useful overall structure, it was not followed rigidly. In this case, the six-month internship duration and internal changes within the organization meant that some of the initially planned activities lost relevance. At the same time, new needs emerged, creating opportunities to participate in engaging projects that were not part of the original chronogram.

As a result, the internship did not develop exactly as a linear execution of the original plan. Some areas, particularly those more directly connected to chatbots, were explored in depth during the first months and then required less follow-up than initially expected. At the same time, new projects emerged, some of them more focused on data querying and visualization. In practice, this meant that the internship gradually became broader than the original plan suggested, so rather than representing a deviation in a negative way, this adjustment allowed the work to remain useful to the organization while also becoming more closely connected to the Master's academic background.

4.3 Initial Experience

The first weeks were especially important for integration into the organizational setting. Although the internship only required attendance at the office on two days per week, a more frequent in-person presence was adopted at the beginning in order to facilitate integration, participate in onboarding sessions organized for the interns to obtain a broader understanding of the company's business model, its departments, and the way those departments interacted with each other. At the same time, the initial period included completing training courses available through the company's learning platform. These courses covered workplace skills, introductory data analytics topics, and the use of AI tools in professional settings, which helped create a stronger foundation for the projects that followed.

This initial stage was key to success, as early investment in organizational familiarization reduced the learning curve and clarified how technical requirements linked to business needs. This was especially important given the involvement of multiple teams and external partners.

4.4 AI Initiatives

4.4.1 User Story Creator

One of the first initiatives presented during the internship was Story Weaver, a GenAI-based tool designed to bridge the gap between business and technical teams. Prior to its introduction, business requirements were submitted as high-level features, often lacking sufficient detail and technical clarity. This required significant effort from TSID team members, particularly Business Analysts and QA, to interpret, refine, and translate those inputs into functional and technical specifications, as well as to define acceptance criteria. This process was time-consuming, prone to misunderstandings, and frequently resulted in change requests due to missing or unclear requirements identified late in the development cycle.

Story Weaver addresses this challenge by leveraging Generative AI to take the features created by business teams and automatically translate business requirements into structured functional and technical requirements. It generates detailed user stories and acceptance criteria, partially automating the work traditionally performed by Business Analysts and QA. By enabling both business and technical stakeholders to communicate in a shared, structured language from the outset, the tool reduces ambiguity, minimizes rework, decreases the number of change requests, and accelerates overall delivery.

As the development of Story Weaver had already been completed before the start of the internship, the contribution to this initiative focused more on the post-deployment phase. The assigned task was to create a feedback form through which users could report errors, limitations, or suggestions regarding the tool’s use. This activity was important because it allowed the collection of structured feedback from users after implementation.

4.4.2 Internal Chatbot

A more substantial involvement occurred in this project, which focused on testing an internal AI chatbot designed to assist employees in accessing information more rapidly on the company’s internal website. The chatbot was expected to respond to questions concerning policies, regulations, product information, videos, and other internal materials, while also presenting the sources used to generate the answer. The project had already reached an initial development stage by the time the internship began, and the solution was being developed in collaboration with external companies. Regular meetings with the teams provided direct exposure to real project monitoring practices and the coordination required when multiple stakeholders contributed to a single digital solution.

The core contribution to this project centered on functional testing. A structured set of questions, mostly written by my supervisor and later by me, were used to evaluate the chatbot's answers. Interactions were recorded in Microsoft Excel following a pre-defined structure. This type of systematic testing is especially relevant in conversational systems, where quality cannot be assessed only by technical deployment and must be evaluated through realistic prompts, error tracking, and iterative refinement.

The tests revealed several recurring limitations. Among the most frequent issues were the chatbot's inability to retrieve certain documents, hallucinated answers when the system should have indicated uncertainty, incorrect citation links, inaccurate timestamps in video-related responses, slow response times, and answers based on outdated documentation. The tests served as a structured validation mechanism that made visible which categories of error were affecting the tool's reliability, usability, and trust. As a result, the project team gained clearer evidence on where corrections were most needed before broader internal deployment.

During this testing phase, the possibility of automating part of the work was also considered. The underlying idea was to use Python to automatically submit predefined questions via the chatbot interface, capture the corresponding answers, and export them to a spreadsheet for later manual validation. At the exploratory stage, two tools appeared especially relevant: Playwright and Botium. Playwright enables browser automation for testing and scripting, supports Python (Microsoft, n.d.), while Botium is specifically oriented toward conversational AI testing, relying on a stack built around connectors, scripting formats, and dedicated tooling for chatbot test cases (Botium, 2023). From the perspective of the needs identified in this internship, Playwright seemed the more appropriate option because the objective was not to test a chatbot through a direct connector or a dedicated conversational testing stack, but rather to automate interactions with an existing web interface and capture the outputs in a relatively flexible way (Microsoft, n.d.).

I chose not to pursue automation due to security, effort, and limited long-term gains. As the chatbot project matured, developing custom testing automation was not justified by its remaining lifespan. This highlights a key lesson of the internship that sometimes the most technically interesting solution isn't always the best. Often, the best decision balances efficiency, risk, timing, and maintainability.

Although the final solution was not the result of the internship work alone, the testing activities helped increase its reliability before release and clarify issues that the development team needed to correct.

4.4.3 Customer Support Chatbot

While still involved in the internal chatbot project, participation also began in a second AI initiative, this time oriented toward customer support. Compared with the internal chatbot, this project had a narrower but more operationally sensitive objective to assist the customer support team in resolving POS terminal issues more efficiently. The solution relied on documentation stored in SharePoint, organized by machine brand and model, and was designed to support agents during live phone call customer interactions. In practical terms, the chatbot was expected to reduce search time, provide solutions based on available documentation, and display the references used in the answer.

The testing approach adopted for the chatbot followed the same structure as that used in the previous project, again using Excel. In addition, the project involved weekly meetings with the external development partner and, in some cases, direct interactions with the main developer to present detected issues and understand how the corrections were being implemented. This was particularly valuable for learning because it made the relationship between test evidence and technical correction more visible.

The test results showed that the chatbot's performance was highly dependent on the quality and structure of the source documentation. Problems emerged when documents were poorly organized, when image-heavy content was difficult for the system to interpret, or when certain brands were not being recognized properly. In the initial stages, the chatbot also struggled to interpret the brand and model within the same message, forcing operators to split the interaction into separate steps and reducing conversational fluidity. These findings highlight a key principle of AI decision support, the output value depends on the quality, consistency, and interpretability of data and documentation.

The conclusion of the project, after several months of development, meant that the testing process successfully supported its maturation. The positive contribution of the internship in this context lay mainly in identifying failure points, structuring test documentation, and strengthening communication between business-side validation and technical implementation.

4.4.4 AI Benchmark for Customer Service

While the chatbots were still under testing, an additional task was preparing a benchmarking presentation on the use of artificial intelligence in customer service. This assignment complemented the more operational testing work with a broader strategic perspective by requiring UNICRE's initiative to be positioned within the wider context of AI adoption across industries. The starting point for this presentation was a market-dispersion exercise based on sources previously identified together with the internship supervisor. Drawing from Deloitte's 2025 MarginPLUS Survey, which considered 397 high-level executives from different industries and geographies in 2024, the most common objective behind AI adoption was efficiency (39%), followed by the enhancement of customer experience (27%) and the acceleration of innovation (19%), while the remaining 15% corresponded to other objectives. The same source also indicated that despite these ambitions, only 21% of organizations had exceeded their annual savings targets, largely due to unstable infrastructure, rigid cost models, and outdated systems. In addition, the benchmark highlighted that the organizations leading the market tended to distinguish themselves by setting more ambitious targets and sustaining investment, even when this meant not prioritizing short-term cost reduction to remain at the forefront of innovation. From a functional point of view, AI was being used most frequently in customer support (55%), sales and marketing (55%), and technology or cybersecurity (47%). Among these areas, customer support was identified as the function with the highest expected value potential (29%)(Deloitte's 2025 MarginPLUS Survey, Deloitte Development LLC). Taken together, these findings reinforced the strategic relevance of continuing to invest in AI-enabled support solutions, including chatbot initiatives for customer service.

A second stage of the presentation focused on the various ways AI can be integrated into customer support workflows. For this part, the benchmark materials relied primarily on McKinsey's 2025 discussion of agentic AI and on the associated workflow distinctions used in the project. Three broad configurations were considered:

i. **Human-assisted workflow:** AI supports by providing information, suggestions, or content, but the human operator retains decision-making, validating, inspecting, and adjusting the output; according to the benchmark notes, this type of workflow is associated with an average resolution-time reduction of 5% to 10%.
ii. **AI-augmented workflow:** the relationship becomes more collaborative, AI assumes repetitive or lower-value tasks, allowing the human worker to concentrate on experience-based judgment and problem solving, with average reductions estimated at 20% to 40%.
iii. **Agentic workflow:** AI becomes capable of planning and executing substantial parts of a workflow with limited human intervention, requiring supervision mainly in exceptional situations; in the benchmark materials, this configuration was associated with potential work-time reductions between 60% and 90%.

McKinsey's 2025 AI survey found that 88% of respondents use AI in at least one function, but only 39% are testing agentic workflows(Seizing the agentic AI advantage, McKinsey, 2025). This shows that AI adoption is widespread, but autonomous workflow integration still remains in its early stages. The key takeaway from the benchmark presentation was that long-term value is best realized through a gradual shift from isolated AI support to more integrated, and when suitable, more autonomous support models that can handle larger parts of a process from start to finish.

After establishing this conceptual overview, the work moved to a more concrete market-mapping exercise focused specifically on customer service. An Excel file was created with three separate worksheets representing the sectors selected for analysis: banking, supermarkets, and e-commerce. Within each worksheet, the cases were organized using a common structure that included the company name, the type of assistant, the solution name, general functionalities, more innovative functionalities, additional notes, and the source consulted. The benchmark also distinguished between Portuguese companies and major international companies to support both local comparisons and broader market observations. More than forty different assistants were initially registered in this file. After this first screening, the supervisor selected the most relevant cases for inclusion in the final presentation. One of the practical objectives was to compare these market examples with UNICRE's own uGenie chatbot for POS customer support, identifying not only where the solution already showed positive alignment with market trends, but also where there was room for improvement in functionality, autonomy, and overall service value.

From an internship perspective, this task contributed to a more informed understanding of how AI initiatives in customer service can be assessed not only technically but also strategically and comparatively. On the one hand, the benchmark supported the idea that continued investment in AI for customer support was consistent with broader market priorities and with the areas where organizations expected to create the most value. On the other hand, it showed that the maturity of AI adoption still varies considerably across organizations, particularly as organizations move from assisted tools to more autonomous workflows. The result created a structured basis for internal reflection on the company's current position, the direction in which chatbot solutions may evolve, and the improvements that could make future implementations more competitive and operationally relevant.

4.5 Customer Area Development Testing

In the final months of the internship, participation also extended to testing newly implemented pages on the customer area website. Although technically less complex than the chatbot initiatives, this activity remained relevant because it involved verifying developments based on the requests documented in user stories, verifying that functionalities behaved correctly, comparing the UX and UI of the implemented pages with the planned designs, as well as suggesting improvements when necessary.

A positive aspect of this activity was the communication dynamic surrounding it. Since these developments were implemented by a member of the Digital Experience & AI team, the validation process was more immediate and interactive. Issues could be discussed in real time, accelerating correction cycles and reducing the distance between testing and implementation. This type of testing reinforced important professional skills, particularly attention to detail, alignment between requirements and final output, and the ability to communicate observations clearly in a development context.

4.6 Data Querying and Extraction

Another early project involved a collaboration with a data analytics firm specializing in business solutions. UNICRE engaged with this partner to develop a churn prediction model for its acquiring sector.

The main responsibility was to query, extract, and prepare data for the model. During scoping meetings prior to joining the project, the necessary tables and fields were identified. Using a secure virtual machine with SAS Enterprise Guide, the typical ETL tasks were performed, including joining and filtering tables from UNICRE's huge data warehouse. The focus was on historical transactions within a single business sector to keep the initial model testing manageable. Tasks included writing queries to extract specific columns, apply date and sector filters, and save the results for the analytics team.

At first, this was quite daunting. Many tables contained millions of rows, so opening them in raw form often caused SAS EG to crash. It was crucial to learn to apply filters early (for example, limiting dates before loading) and to use inner joins progressively to reduce the sizes of intermediate tables. At first, many challenges arose. The app would crash randomly; some extractions were still so large that they took several hours to complete or had to be split into many smaller extractions; some field names were ambiguous, making interpretation harder; and a simple mistake in join definitions resulted in hours of lost work. These errors were only discovered by comparing output row counts against expectations, by the supervisor's feedback when predicted values did not align or only when the team started using the extractions for the creation of the models.

Communication was maintained through weekly meetings with the external analytics firm. While those meetings mainly focused on the vendor's ongoing modeling progress, they also provided opportunities to discuss data issues and clarify the business context. The firm's team also interacted with various UNICRE departments to understand key customer segments and priorities, for example, learning how different teams measure customer value.

The data extraction phase initially lasted about two weeks. After the initial model run, a follow-up extraction week was needed a few months later to refine the dataset and fix any remaining issues. In the end, the intern attended an in-person review meeting where the responsible team presented the final churn model output. The results were successful, the model met its preliminary goals for the test sector. This positive outcome validated the data preparation work.

4.7 Dashboard Development

Hands-on training in Power BI was provided, initial tasks included guided exercises and exploration of sample dashboards made available by the supervisor. This practical learning was essential, as there was no prior experience with Power BI. The supervisor allowed practice with sanitized data in example reports to develop an understanding of how queries and visualizations work.

4.7.1 Collaborator Grading Dashboard

An existing Power BI report tracked the resolution of IT issues logged in Azure DevOps. Each issue had a priority level and was assigned to a collaborator. Collaborators were graded on response and resolution speed, with grades, where faster handling earned higher grades, and the time frames were correlated with urgency. The first task on this dashboard was to verify and correct the DAX calculations used to compute these grades after an inconsistency in the grade values had been identified.

Upon inspection, it was discovered that the DAX measures did not handle missing dates properly. Some issues did not yet have a resolution date (if unresolved) or even an activation date, yet the original measure logic treated these blanks as numeric zeros. This skewed the grade averages. The DAX code was modified so that any missing end date would result in a blank grade rather than a numeric value. Furthermore, the final grade measure was improved by counting only the valid components, and the average was calculated by dividing by the number of valid grades rather than a fixed denominator. This ensured that missing entries no longer skewed averages incorrectly.

Another improvement was added for time-based filtering, which was relevant since the slicer on this dashboard operates by semester. To ensure it filtered correctly for both issue creation and resolution dates, two separate date fields were created, one for activation and one for resolution. Each was linked to the calendar table via an inactive relationship. Then, in the relevant measures, the USERELATIONSHIP function was used to activate the correct relationship for each context. This change made the semester filter behave correctly on each page (active vs. closed issues).

With these fixes, the dashboard now produces accurate grades for both response and resolution performance. The results can reliably inform managers about which collaborators and issue types are meeting targets. This task ensured that UNICRE's executive team could confidently use the issue metrics in that way.

Figure 1: Issues Reaction time Grading Page

Figure 2: Solved Issues Grading

4.7.2 TSID OPEX and CAPEX Dashboard

The following task involved creating new pages within an existing dashboard to track TSID's OPEX and CAPEX costs. The dashboard included three main pages, each showing four key performance indicators (KPIs): the budget, the remaining allocated budget not yet spent, the amounts paid, and the residual balance, which is the difference between the budget and the paid amounts. The first page provided a summary of CAPEX, featuring two stacked column charts that show the relationship among the budget, allocated budget, and balance for OPEX projects. The second page offered a detailed view of OPEX, including a similar stacked column chart without the balance and three pie charts. These pie charts displayed the top seven projects by highest budgets, balances, and allocated budgets. The task was to replicate a page that duplicated the OPEX detailed view but focused on CAPEX instead, which was straightforward, though the key challenge was identifying the corresponding CAPEX values.

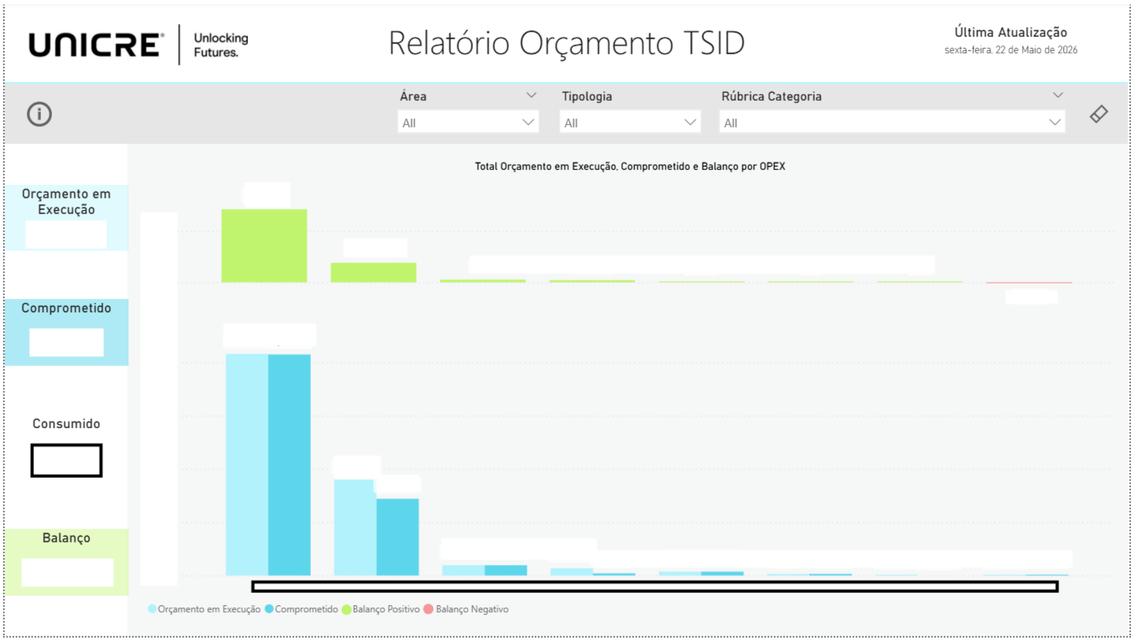

Figure 3: Overview OPEX

A few months later, a new request was received for that dashboard: two pie charts on the detail page, showing the top 7 projects by highest budget and top 7 by allocated budget, were to be replaced by a pie chart of negative balances, and the CAPEX overview page was to include a new slicer to filter by project business area.

To add the project-area slicer on the CAPEX page, the field was first added to the page. When no values appeared, this most likely indicated a data issue. Investigation revealed that the existing CAPEX dataset did not include the area field. The solution was to change the data that was being used.

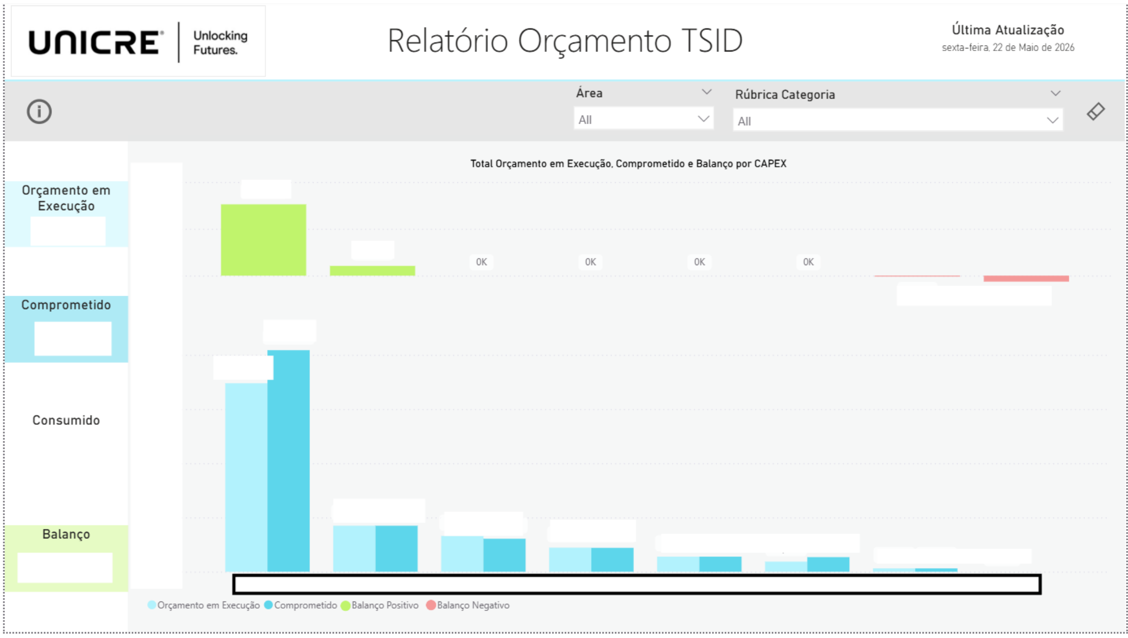

Figure 4: Overview CAPEX

On the detail page, the requirement to add a negative-balance pie chart and reformat the colors posed a technical challenge. Power BI does not allow conditional color formatting in pie or donut charts by default. Initially, each project in the pie was manually assigned a color. However, applying page filters caused the colors to shift incorrectly because the filters changed the set of data points, and manual color assignments no longer matched. After some trial and error, a workaround was found: first apply a conditional color gradient to a standard bar chart (which Power BI allows), then switch the visual type to a donut chart. This preserves the assigned colors for each category even when filters change the order. The chart type was also changed to a donut for clarity. With this approach, the negative-balance donut correctly displays each project with a unique, consistent color.

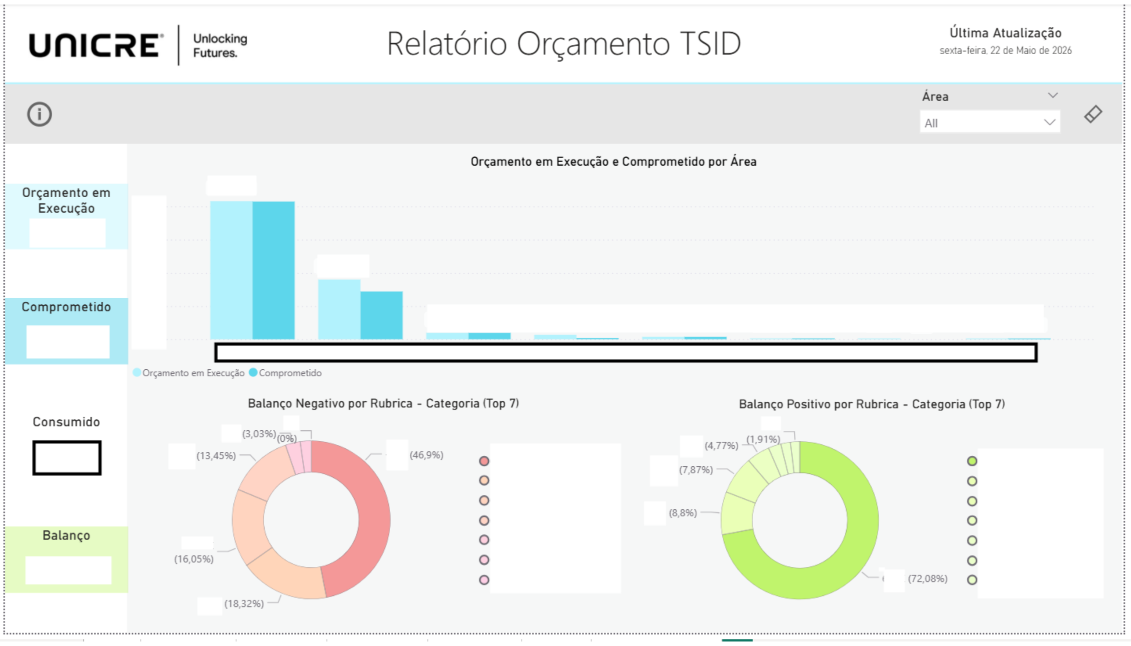

Figure 5: Detailed Overview OPEX

In the end, the enhanced dashboard included the requested visuals, one donut chart of negative balances by project, and, on the overview page, a slicer filtering CAPEX data by project area. These additions improved the dashboard's interactivity and met the company's needs.

4.7.3 Commercial Team Reporting Dashboard

The final Power BI project was built entirely from scratch. Its purpose was to automate the monthly presentation used by the commercial team to monitor the promotion of REDUNIQ solutions to possible clients. Previously, this report was assembled each month manually in PowerPoint; the new approach was to consolidate everything into a dynamic dashboard that simply needed a data refresh.

The data sources were Excel files containing the required metrics that were provided to me. Initial data wrangling was performed in Power Query, including basic tasks such as renaming columns, removing duplicates, and correcting data types. Two of the required data queries were found to be missing crucial information, as they lacked a link between product solutions and client activities. To address this issue, HUE SQL Editor was used to examine the database tables and identify the required joins. A corrected SQL query was then written to extract the data with all necessary fields.

The dashboard comprises five pages:

- **Page 1 – KPIs:** Four main KPIs are displayed: total accesses, total simulations (customer quotes generated), total offers presented, and simulation-to-offer conversion rate. For each KPI, the dashboard shows the current-period total value, the previous-period total value, and the percentage change (increase or decrease). Most values are simple column totals. A special DAX measure was created to compute the period-over-period change: it calculates the percentage difference and includes a "+" or "–" sign to indicate an increase or a decrease. This gives managers at-a-glance insight into trends.

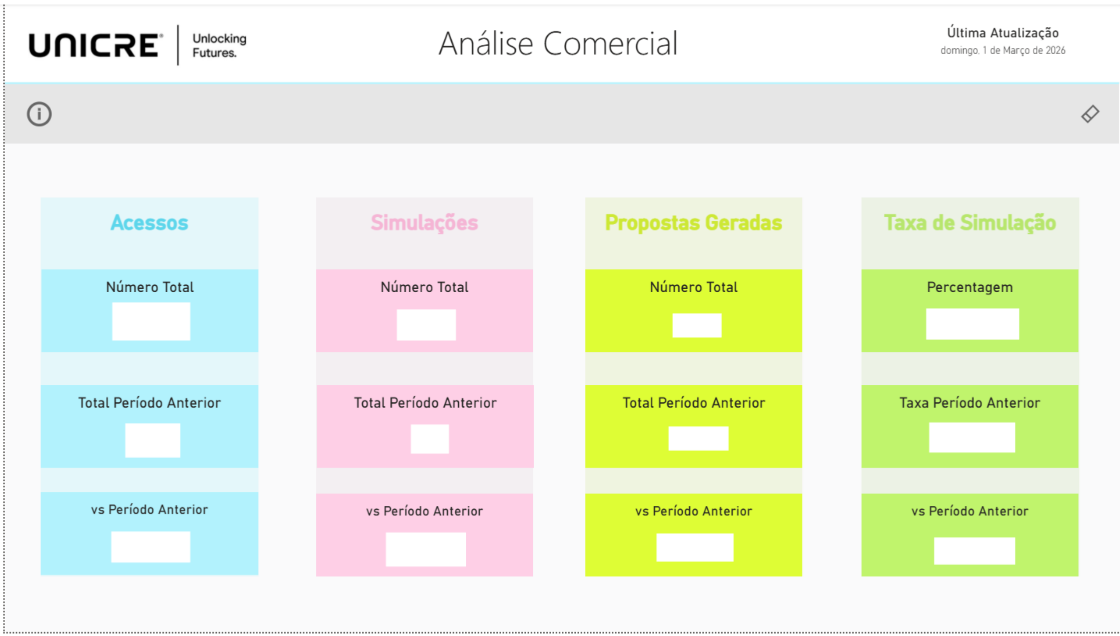

Figure 6: Main KPIs

- **Page 2 – Time Series:** Each of the first three KPIs is plotted as a daily line chart across the current monthly period. A slicer allows filtering the entire page by any of the KPIS. At the bottom of this page, four additional measures are displayed: peak daily accesses, average daily accesses on working days, total accesses, and the number of days with zero accesses (the only zero-access days are weekends). These supplementary figures highlight performance peaks and gaps.

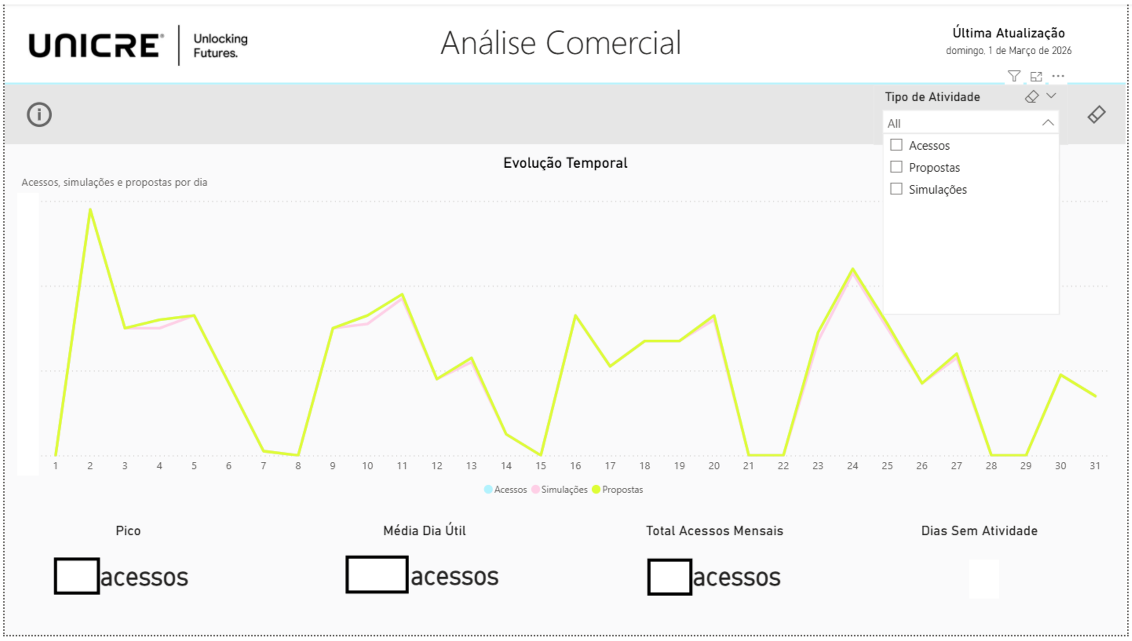

Figure 7: KPIs Evolution Over Time

- **Page 3 – Offers Status and Access by Region:** One stacked bar chart shows the number of offers in each status category (incomplete, negotiation, denied, approved). A second stacked bar chart shows total accesses broken down by each collaborator's geographic region. These visuals help the team see where prospects are located and how far along deals are.

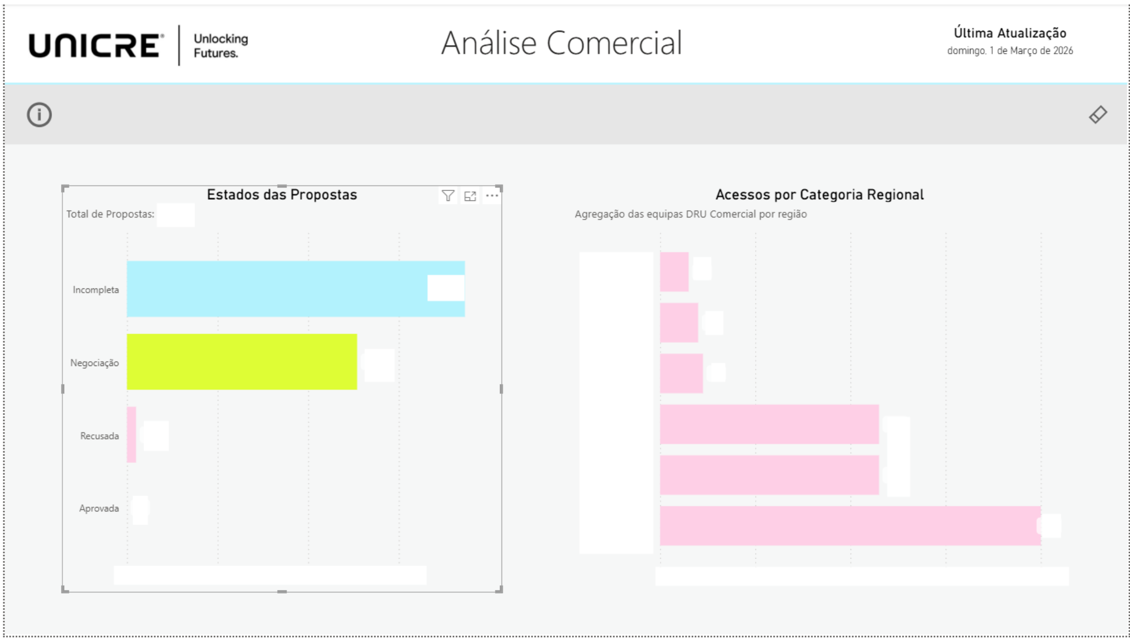

Figure 8: Offer and Access by Region

- **Page 4 – Relationship between Offers and Solution:** A stacked column chart depicts the total number of offers for each product solution. A slicer lets the user filter this chart by solution type (there are two types of REDUNIQ solution). Two card visuals display the total number of offers for each solution type alongside the chart.

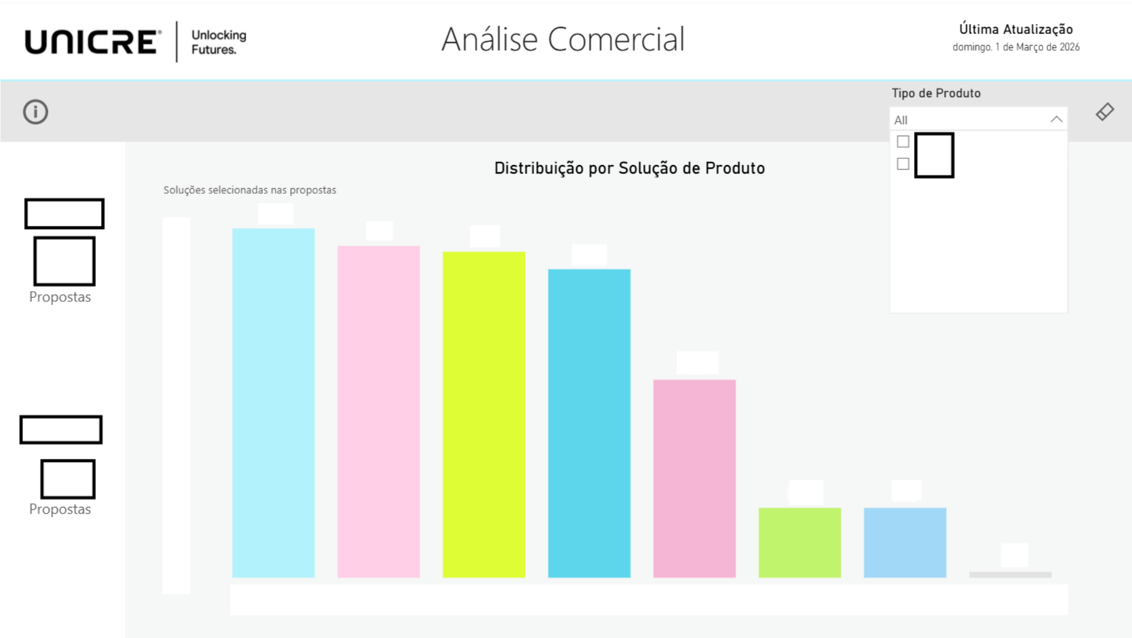

Figure 9: Offers by Solution

- **Page 5 – Top Collaborators:** This table lists the top 15 collaborators ranked by number of accesses. It includes columns for the collaborator's name, email, team, and their totals for simulations and offers. This makes it easy to recognize the most active salespeople and their outputs.

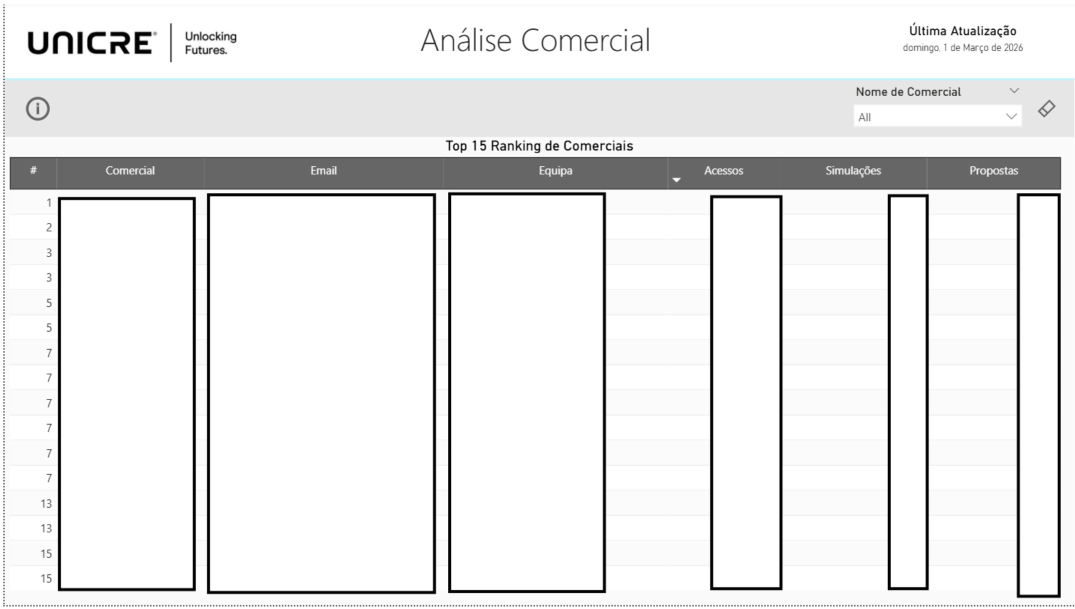

Figure 10: Top Commercials Table

By completing this dashboard, the need for manual slide preparation was eliminated. Each month, the Power BI report automatically refreshes all visuals, which is expected to significantly reduce manual effort. Now, these interactive dashboards allow directors to effectively compare performance and make data-driven decisions; the new dashboard empowers the commercial team to spot trends and adjust strategy.

4.7.4 Additional Power BI Training

Finally, regarding the use of Power BI, UNICRE provided the opportunity to attend a two-month certified intermediate Power BI training, with two classes each week, which went on after the end of the internship. This experience helped me learn new features, including Power Query, which I had not explored in depth in my past dashboard projects.

5. Conclusion

This internship offered a valuable chance to utilize the skills gained during the Master's in Management Information Systems in a real organizational setting marked by continuous digital transformation and technological innovation. At UNICRE, the experience involved work in Business Intelligence, data analytics, artificial intelligence, testing, and decision support, providing insight into both the technical and organizational aspects of information systems.

The work carried out underscored the growing importance of data-driven decision-making and AI-supported processes in modern organizations. Through participation in chatbot initiatives, customer area testing, data extraction projects, and dashboard development, it became clear that technological solutions deliver the greatest value when supported by reliable data, well-structured processes, and continuous validation. Testing AI solutions highlighted both the potential and the limitations of generative AI, particularly regarding response accuracy, hallucinations, source reliability, and documentation quality. At the same time, benchmarking activities provided a broader understanding of how organizations are adopting AI to improve efficiency, customer experience, and operational performance.

From a Business Intelligence perspective, developing and enhancing Power BI dashboards reinforced the importance of transforming large volumes of data into accessible, actionable information. The dashboards created during the internship contributed to process automation, improved visibility of key performance indicators, and reduced the manual effort associated with reporting activities. Similarly, the data extraction activities supported the development of predictive models, demonstrating the relevance of data preparation and quality in analytics projects.

The experience also enabled the development of important professional personal competencies. Technical skills were strengthened through the use of SQL, SAS EG, HUE, Power BI, Power Query, and AI-related tools. In parallel, soft skills such as communication, teamwork, problem-solving, attention to detail, adaptability, and stakeholder collaboration were continuously exercised through interactions with different departments, external partners, and multidisciplinary teams. Exposure to project discussions, testing cycles, and organizational change processes also contributed to a broader understanding of how information systems initiatives are managed in practice.

Several strengths were evident throughout the internship. The organization provided access to diverse projects, modern technologies, supportive supervision, and opportunities to collaborate with different business areas. The hybrid work model also promoted a balance between autonomy and teamwork. Additionally, participation in a certified Power BI training program reflected the organization's commitment to continuous learning and professional development. Nevertheless, some limitations were observed. Organizational restructuring during the internship led to changes in priorities and project directions, while certain AI initiatives faced challenges related to documentation quality and reliance on external development partners. However, these situations also provided valuable learning opportunities by exposing the realities and complexities of digital transformation projects.

The objectives established before the internship were achieved to a significant extent. Support was provided to the execution and monitoring of Generative AI projects through participation in chatbot initiatives and benchmarking activities. Practical skills in testing, evaluation, and validation of AI solutions were developed through extensive functional testing and issue identification. Exposure to project coordination processes was obtained through regular meetings with internal teams and external partners. Collaboration with various stakeholders contributed to discussions on user experience and chatbot adoption, while participation in testing and knowledge-base activities supported the continuous improvement of AI solutions.

In conclusion, the internship successfully fulfilled its purpose of bridging academic knowledge and professional practice. The experience demonstrated how Business Intelligence and Artificial Intelligence can support organizational performance, improve decision-making processes, and contribute to digital transformation initiatives. Beyond the technical outcomes achieved, the internship provided a comprehensive understanding of the challenges and opportunities in information systems management, serving as an important step in professional development and future career progression.

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