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Process Mining and Power BI for KPI Monitoring in Higher Education Institutions

Master's Degree in Data Science

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Project developed under the academic supervision of Professor Ricardo Martinho.

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Abstract

The increasing digitalization of administrative activities in Higher Education Institutions (HEIs) has generated large volumes of process data stored in several information systems. While these systems ensured traceability and accessibility of information, they often lacked systematic monitoring of business process performance, making it difficult to identify inefficiencies, deviations or bottlenecks. This gap makes it difficult for stakeholders to make data-driven decisions and limits the opportunities for continuous improvement.

This work addressed the problem of limited visibility over the execution and efficiency of business processes within a HEI by applying Process Mining techniques combined with Business Intelligence (BI) visualizations. The aim was to extract, process and analyze process-related data from the institution's management information systems, identify relevant performance indicators and provide decision-makers with actionable insights through interactive dashboards.

The solution involved process Key Performance Indicators (KPI) definitions, which were grouped into temporal, volume-based, cost efficiency and compliance categories, i.e., KPIs that measure whether the real execution of a process followed the intended process model. Using Process Mining, KPIs related process metrics were discovered and calculated, enabling the identification of deviations and potential optimization points.

Beforehand, a validation session with institutional stakeholders occurred, where the practical value of the KPIs for supporting operational and strategic decisions was confirmed. Additionally, the process mining analysis revealed patterns that were previously unknown to managers, reinforcing the benefits of integrating analytical techniques into daily process monitoring.

For visualization purposes, three interactive dashboards were developed in Microsoft Power BI, presenting process execution times, workload distribution, cost indicators and other relevant metrics.

The developed solution successfully provided a clear, data-driven overview of the institution's business processes, highlighting areas of inefficiency such as excessive idle times, which affect the costs of each process, and frequent process deviations.

In conclusion, the project demonstrated that the combination of Process Mining and Business Intelligence tools can effectively enhance process transparency and performance monitoring in HEIs.

Resumo

O aumento da digitalização das atividades administrativas nas Instituições de Ensino Superior (IES) tem gerado grandes volumes de dados de processos armazenados em diversos sistemas de informação. Embora estes sistemas assegurem a rastreabilidade e a acessibilidade da informação, muitas vezes carecem de mecanismos sistemáticos de monitorização do desempenho dos processos de negócio, dificultando a identificação de ineficiências, desvios ou constrangimentos. Esta lacuna limita a capacidade de tomada de decisão baseada em dados por parte dos *stakeholders* e reduz as oportunidades de melhoria contínua.

Este trabalho abordou o problema da visibilidade limitada sobre a execução e eficiência dos processos de negócio numa IES, através da aplicação de técnicas de *Process Mining* combinadas com visualizações de *Business Intelligence* (BI). O objetivo foi extrair, processar e analisar dados relacionados com processos a partir dos sistemas de informação de gestão da instituição, identificar indicadores de desempenho relevantes e disponibilizar aos decisores informações acionáveis por meio de dashboards interativos.

A solução desenvolvida envolveu a definição de *Key Performance Indicators* (KPIs), agrupados em categorias temporais, de volume, de eficiência de custos e de conformidade, ou seja, indicadores que medem se a execução real de um processo seguiu o modelo de processo pretendido. Com o uso de *Process Mining*, métricas associadas a estes KPIs foram descobertas e calculadas, permitindo identificar desvios e potenciais pontos de otimização.

Previamente, foi realizada uma sessão de validação com *stakeholders* institucionais, onde foi confirmada a utilidade prática dos KPIs no apoio a decisões operacionais e estratégicas. Adicionalmente, a análise de *Process Mining* revelou padrões anteriormente desconhecidos para os gestores, reforçando os benefícios de integrar técnicas analíticas no acompanhamento diário dos processos.

Para efeitos de visualização, foram desenvolvidos três *dashboards* interativos em Microsoft Power BI, que apresentam tempos de execução, distribuição de carga de trabalho, indicadores de custo e outras métricas relevantes.

A solução desenvolvida forneceu, com sucesso, uma visão clara e baseada em dados sobre os processos de negócio da instituição, destacando áreas de ineficiência, como tempos de espera excessivos, que afetam os custos de cada processo, e desvios frequentes.

Em conclusão, o projeto demonstrou que a combinação de ferramentas de *Process Mining* e *Business Intelligence* pode, de forma eficaz, reforçar a transparência dos processos e a monitorização do desempenho nas Instituições de Ensino Superior.

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List of Abbreviations

AI	Artificial Intelligence
BI	Business Intelligence
BPM	Business Process Management
ESTG	Escola Superior de Tecnologia e Gestão
ETL	Extract, Transform, Load
HEIs	Higher Education Institutions
KPIs	Key Performance Indicators
OU	Organizational Unit
PSSUQ	Post-Study System Usability Questionnaire
PUL	Polytechnic University of Leiria
RPA	Robotic Process Automation

1. Introduction

This project presents the work developed within the scope of the final project of the Master's Degree in Data Science at the School of Technology and Management, Polytechnic University of Leiria. The project is framed in a real-world context and aims to explore, design, and implement advanced technological approaches combining Process Mining and Business Intelligence methodologies.

The main objective is to enable the monitoring, analysis and subsequent optimization of organizational processes by leveraging data-driven insights. Through the integration of Process Mining techniques, it becomes possible to reconstruct and visualize the actual execution of processes, identify inefficiencies and detect deviations from the intended workflows. Complementarily, Business Intelligence tools are employed to structure and present the extracted information in a meaningful way, supporting decision-making and promoting continuous process monitoring and improvement.

1.1. Context and Motivation

Higher Education Institutions (HEIs) are complex organizations where administrative, academic and financial processes coexist in a highly bureaucratic environment. These processes, ranging from student enrolments and course approvals to staff management and financial requests, generate large amounts of data. Much of this data is recorded in management information systems, which guarantee traceability and accessibility. However, these systems usually lack mechanisms for continuous process performance monitoring and systematic analysis of efficiency, deviations and bottlenecks [1].

Recent studies confirm that the efficiency of administrative processes in HEIs has received increasing attention, although in a fragmented manner. A scoping review of the literature shows that existing approaches often focus on specific indicators or isolated analyzes, without providing an integrated view to support real-time decision-making [1]. At the same time, the massive digitalization of institutional processes and the growing volume of data highlight the need for solutions that combine big data management with accessible analytical tools, such as Business Intelligence (BI) dashboards [2].

In this context, decision-makers often face limited visibility over how processes are executed, how long they take and where inefficiencies occur [1,3]. The absence of monitoring tools restricts their ability to make timely and evidence-based decisions. At the same time, the growing demand for transparency and efficiency in public institutions requires solutions that go beyond static reports, enabling the automation of monitoring tasks and the proactive identification of improvement opportunities [2].

The core problem addressed in this study is the inability to efficiently assess and improve internal administrative processes. Without a unified view of process performance, identifying inefficiencies and implementing targeted improvements becomes a challenge [4].

The primary objective of this study is to implement a process monitoring solution that is directly connected to the institution's data sources and supported by process mining techniques. Continuous monitoring has been recognized as a critical stage in the BPM lifecycle, ensuring that operational insights can be systematically used to improve organizational performance [5]. By automating the linkage between process data and analytical models, the project provides institutional decision-makers with a dynamic tool capable of delivering continuous, data-driven insights. Prior research has shown that dashboards are effective in transforming raw data into actionable information for managers [6], and they have been increasingly adopted in higher education to address challenges of transparency and efficiency [2]. In this sense, the solution proposed in this study not only supports the detection of deviations from expected process models and performance expectations but also contributes to the broader institutional goal of improving transparency, efficiency, and strategic management of business processes [3,4].

This project was developed in close collaboration with Bruno Vieira Silva, a student in the Master's Programme in Computer Engineering – Mobile Computing at the Polytechnic University of Leiria. His master's project, titled *"Implementation of a Data Warehouse and Process Mining Techniques for Process Analysis at the Polytechnic of Leiria"*, focuses on the backend components of the data architecture. His contributions to this project include the ingestion of raw datasets into a centralized data warehouse, the execution of exploratory data analysis, data cleaning and transformation, and the integration of the prepared data into Microsoft Power BI. This collaborative framework ensures methodological rigor by clearly delineating responsibilities between data engineering and the analytical modelling and visualization components of this research.

Ultimately, the project aims to deliver a comprehensive suite of dashboards that combine operational performance indicators and economic metrics. These tools will serve to enhance process transparency and efficiency, while also providing valuable managerial support for strategic decision-making within PUL's business processes conducted through the internal document management system or other Information Systems producing process log information.

1.2. Problem Statement

Several studies have addressed challenges similar to those faced at the Polytechnic University of Leiria (PUL), namely the lack of process visibility and monitoring mechanisms within higher education institutions. For example, Rojas et al. (2016) [7] reviewed the application of process mining in healthcare, highlighting how fragmented data sources and the absence of systematic monitoring hinder process optimization. Likewise, Turisová et al. (2018) [8] demonstrated the importance of financial indicators in monitoring process performance, underlining that without structured KPI systems, organizations struggle to control efficiency. Comparable research in educational contexts includes Wagner et al. (2022) [4], who used process mining for study planning and monitoring, showing how the absence of integrated dashboards can obstruct proactive interventions. These examples illustrate that the lack of structured KPI monitoring is a widespread issue across domains, reinforcing the relevance of addressing this gap at PUL.

The primary challenge faced by the organization lies in the insufficient visibility and lack of integration among its various internal processes. This fragmentation of data across disparate systems and sources results in significant obstacles to acquiring a comprehensive and unified perspective on overall process performance. Consequently, it becomes inherently difficult to accurately identify inefficiencies, bottlenecks and areas requiring improvement within the operational workflow. Furthermore, this disjointed data landscape hampers the ability of decision-makers to formulate well-informed strategies and interventions based on holistic insights.

Compounding this issue is the absence of integrated and dynamic dashboards or reporting tools that could consolidate key performance indicators in real-time. The lack of such centralized monitoring mechanisms not only impedes effective performance tracking but also undermines timely responses to deviations and emerging challenges. In summary, the current state of fragmented information flow and deficient analytical infrastructure significantly constrains the organization's capacity for process optimization and strategic management.

At the moment, the Polytechnic University of Leiria relies on a Document Management System to support a significant number of its administrative procedures. This system records the different stages of execution, the participants involved, the timestamps associated with each activity and the data generated along the lifecycle of each case. While this ensures basic traceability of processes, it does not provide the means for systematic monitoring.

Until now, there were no mechanisms in place to evaluate these processes from different perspectives, such as control-flow, human resources, execution times or even costs. In addition, there was no organized way of accessing or maintaining the process data in a centralized repository suitable for structured analysis and monitoring.

This situation brings several limitations. The fragmentation of data across different systems makes it difficult to gain a comprehensive view of process execution, hindering the identification of inefficiencies, bottlenecks and deviations from expected workflows. Moreover, the absence of integrated and dynamic dashboards or reporting tools prevents decision-makers from consolidating key performance indicators in real time. As a result, the institution lacks the capacity to track performance effectively, to respond promptly to deviations, and to systematically pursue process optimization.

Therefore, the current state of fragmented information flow and the lack of analytical infrastructure significantly constrain PUL’s ability to ensure transparency, efficiency and continuous improvement in its internal processes.

1.3. Relation to Existing Work

The use of process mining and business intelligence (BI) for monitoring institutional workflows has been extensively studied across domains, though applications in higher education are still emerging. This project builds on several strands of prior research, while extending them to the specific context of administrative processes in HEIs.

Orlovskyi and Kopp (2020) [9] proposed a structured approach to BI dashboard design, emphasizing that dashboards should not be regarded merely as visualization surfaces but as decision-support interfaces that combine usability with data architecture considerations. Their work highlighted the importance of aligning data presentation with cognitive capacities of end-users, a principle that strongly influenced the design choices in this project, where non-technical stakeholders must interpret complex process data in a clear manner.

In the field of process performance analysis, Milani and Maggi (2018) [10] compared various log-based techniques for extracting KPIs from event logs. Their study provided methodological guidance on selecting appropriate indicators depending on data characteristics and analytical goals. This project adopts a similar approach by structuring KPIs into categories such as time, cost, compliance and rework, ensuring that they are both theoretically sound and practically useful.

Complementing this, Yigitbasioglu and Velcu (2012) [6] reviewed dashboard practices in performance management and emphasized design principles that reduce cognitive load, avoid misleading graphics and provide consistent filtering mechanisms. Their findings informed the visualization strategies applied in this work, particularly the prioritization of clarity and comparability across multiple dashboards.

Finally, Wagner et al. (2022) [4] demonstrated the potential of process mining in higher education by combining event log analysis with rule-based artificial intelligence to support study planning and monitoring. Their findings showed how dashboards and conformance analysis can proactively detect deviations in student curricula, underscoring the broader applicability of process mining and BI to educational workflows.

Together, these contributions provide the methodological and practical foundation for this project. While earlier works established principles for KPI definition, log-based analysis and dashboard design, they have primarily focused on corporate or student-centered contexts. This project extends those insights by applying them to document-based administrative processes in higher education, addressing the gap in process monitoring for bureaucratic and resource-intensive workflows.

1.4. Objectives

The overarching aim of this project is not only to analyze institutional processes, but also to design and implement an integrated process monitoring solution for the Polytechnic University of Leiria. By combining process mining techniques with BI dashboards, the project seeks to provide institutional decision-makers with real-time visibility over administrative workflows. The focus is on enabling non-expert users to monitor, analyze and improve inherently highly bureaucratic processes recorded within the institution’s management information systems. In doing so, the project ensures that insights into inefficiencies, deviations and opportunities for optimization are accessible beyond the scope of data science specialists, thus fostering a culture of continuous improvement.

Supporting literature underscores the importance of such integration. Continuous process monitoring is recognized as a critical component of the Business Process Management (BPM) lifecycle, ensuring that operational insights feed directly into process redesign and improvement [5]. Research has also shown that dashboards built on event logs can significantly enhance transparency and accountability in institutional contexts, reinforcing their value as decision-support tools for organizations such as higher education institutions [11].

In line with these perspectives, the specific objectives of this project are as follows:

1. **Dataset characterization and preparation** – Conduct a detailed assessment of datasets extracted from PUL’s document management platform, ensuring data

quality through preprocessing tasks such as cleaning, error correction and standardization. Work carried by Bruno Vieira Silva, who was responsible for preparing and transforming the raw datasets;

2. **KPI definition and validation** – Identify and define relevant key performance indicators based on a combination of literature review, best practices and stakeholder input. These indicators are designed to reflect both operational and strategic dimensions of institutional processes (work carried out by the author of this project);
3. **Application of process mining techniques** – Transform event logs into meaningful insights through methods such as discovery, conformance checking and performance analysis, thereby uncovering patterns, inefficiencies and deviations (work performed by Bruno Vieira Silva);
4. **Implementation of BI dashboards** – Develop interactive dashboards in Microsoft Power BI to make performance indicators and analytical results accessible to non-technical users. The dashboards are designed to support decision-making by combining clarity with interactivity (work carried out by the author of this project);
5. **Validation with stakeholders** – Demonstrate the practical value of the dashboards through validation sessions with institutional users, ensuring that the solution meets real organizational needs and supports evidence-based management (work carried out by the author of this project);
6. **Documentation and knowledge transfer** – Systematically document the methods, tools, analyzes and results in this project report, contributing to institutional process transparency and supporting long-term adoption of process monitoring practices.

In summary, this project aims to bridge the gap between fragmented data sources and actionable insights, leveraging process mining and BI to create a sustainable framework for continuous process monitoring and improvement at PUL.

1.5. Methodological Approach

The main objective of this work will be to design and implement a framework capable of supporting process performance monitoring through the integration of process mining techniques and interactive visualization tools. By doing so, the project will aim to transform raw event log data into actionable insights that can directly support organizational decision-making.

To achieve this, the work will pursue the following specific objectives:

1. **Define a methodological approach** for extracting, cleaning and transforming process event data into a structured format that can be analyzed consistently across different case studies;
2. **Identify and formalize a set of performance indicators** that are both theoretically grounded in the literature and practically relevant for organizations, ensuring that they measure efficiency, effectiveness and resource allocation in processes;
3. **Develop a system of dashboards** that will enable users to interact with the data, explore patterns and monitor process performance in a dynamic way, making it possible to filter by time periods, activities, resources and costs;
4. **Validate the proposed framework through a case study**, in which the methodology and dashboards will be applied to a real-world dataset. The objective here will be to assess not only the technical feasibility of the approach but also its usefulness for practitioners;
5. **Critically analyze the challenges and limitations** encountered during the design and implementation of the framework, highlighting areas where future research can further improve reliability, scalability, and interpretability.

By pursuing these objectives, this work will attempt to contribute both to the academic discussion on process performance monitoring and to its practical application. The expectation is that the proposed framework will help bridge the gap between complex process mining techniques and their effective use by organizations, enabling them to monitor costs, durations, and resource utilization more transparently.

Ultimately, the aim will not only be to develop a functional prototype but also to establish a replicable methodology that could be adapted to other contexts where process performance is a critical factor. This will ensure that the outcomes of the project remain relevant beyond the scope of the case study and may be reused or extended in future research and practice.

1.6. Project Document Structure

This project report is structured into the following chapters:

Chapter 1: Introduces the research context, outlines the underlying problem, and articulates the objectives that guide the development of the project. It also provides an overview of the methodological approach and concludes with a summary of the report's organization;

Chapter 2: Presents the state of the art, offering an extensive review of the existing literature related to document management systems, process performance analysis, and data science methodologies. This chapter explores foundational theories, highlights key technological trends, and identifies methodological frameworks that have been employed in similar contexts. The purpose of this review is to situate the present study within the broader academic discourse, while also identifying relevant knowledge gaps that the current research seeks to address;

Chapter 3: Describes the methodological approach adopted in this study. It outlines the sequence of research activities, including data collection, preprocessing, and indicator selection. Special attention is given to the collaborative aspects of the project, particularly the integration with data engineering processes managed by a partner student. The chapter also discusses the analytical strategies employed to explore the data and ensure the reliability and validity of the findings;

Chapter 4: Dedicated to the definition of requirements and the architectural design of the project. It specifies both functional and non-functional requirements of the dashboards to be developed and details the technological components and software tools selected for implementation. The overall architecture of the data flow, from raw input to visualization, is described, providing insight into how the system supports dynamic and modular analysis of different processes;

Chapter 5: Focuses on the implementation of the dashboards, detailing the construction of both the KPI dashboard and the financial dashboard. This chapter explains the design logic, the visual representation of key indicators and the filter mechanisms applied across the dashboards. In addition, it introduces a process mining map that enables users to view performance and frequency-based visualizations of process flows;

Chapter 6: Addresses the validation phase, in which the dashboards and their respective indicators were evaluated by institutional stakeholders. Feedback was collected to assess the usability, relevance and accuracy of the visualizations, and the chapter discusses how this input informed refinements to the final solution. Functional and usability testing are also presented to demonstrate the robustness of the developed tools;

Chapter 7: Concludes the project by synthesizing the main results, reflecting on the theoretical contributions and practical implications of the research. The chapter also discusses the limitations encountered and outlines potential directions for future work.

2. State of the Art

This chapter will provide the theoretical foundations that support the development of the proposed framework. It will begin by presenting the key concepts of process mining and performance monitoring, followed by an overview of the main techniques and models described in the literature. Special attention will be given to process performance indicators, since these form the basis for the methodological approach adopted in this work. In addition, the chapter will highlight relevant challenges reported by previous studies, establishing the context for the research problem and guiding the methodological decisions presented in later chapters.

2.1. Background

2.1.1. Business Process Management

Business Process Management (BPM) is widely recognized as a discipline that integrates methods, techniques and tools to support the design, enactment, monitoring and improvement of organizational processes. One of the most influential contributions to BPM theory is the definition of the BPM lifecycle, which provides a structured view of how processes should be continuously managed and improved [12].

The BPM lifecycle can be divided into several interconnected phases [12]:

1. process design;
2. system configuration and enactment;
3. execution and monitoring;
4. analysis and diagnosis;
5. process improvement.

This cycle emphasizes that BPM is not a one-time effort, but rather a continuous loop where insights from execution feed back into redesign and optimization.

Later contributions refined this view by demonstrating how process mining techniques can bridge the gap between theoretical models and operational reality. Existing BPM systems often lack comprehensive support for the full lifecycle, particularly in the stages of monitoring and analysis. Process mining techniques, including process discovery, conformance checking, and performance analysis, offer a data-driven approach to address this gap, ensuring that process models more accurately reflect actual operational behavior [13].

A critical perspective on BPM highlights that many initiatives tend to stop at process modelling and automation, overlooking the crucial monitoring and improvement phases of the lifecycle. The true goal of BPM, however, is not simply to represent or automate processes, but to achieve measurable gains in efficiency, compliance and transparency [14].

More recent studies present a comprehensive view of BPM, consolidating its main use cases and demonstrating how lifecycle phases can be enhanced through advanced techniques such as conformance checking and predictive analytics. This perspective reinforces BPM as an iterative cycle in which data is continuously leveraged to refine process models and support informed decision-making [5].

Figure 1 below illustrates the BPM lifecycle adapted from Van der Aalst's work, showing the main phases and their iterative nature.

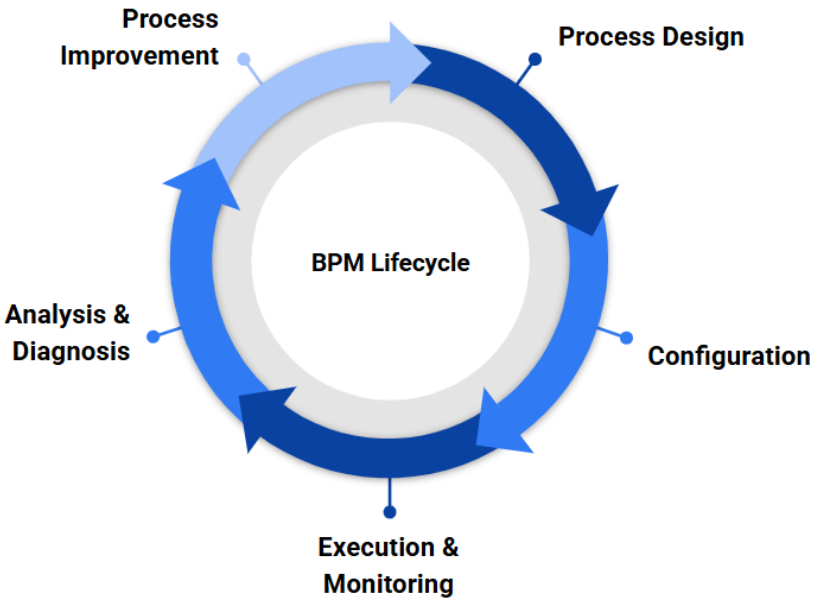

Figure 1- Business Process Management lifecycle [5]

For this project, the BPM lifecycle provides the conceptual foundation for the developed solution. The implemented dashboards correspond particularly to the monitoring and analysis phases, enabling the detection of inefficiencies, bottlenecks and deviations from expected process models. Furthermore, by providing institutional decision-makers with accessible insights, the dashboards also contribute to the improvement stage, facilitating evidence-based interventions and closing the loop of the BPM cycle.

2.1.2. Process Mining and Process Monitoring

Process mining has emerged as a key discipline within business process management, providing data-driven methods for understanding how processes are executed in practice. At its foundation lies the event log, a structured dataset that records the execution of process instances, typically including attributes such as case identifiers, activity names, timestamps and sometimes resource or cost information. Event logs are indispensable because they enable the reconstruction of process behavior from real data, rather than relying solely on predefined models [10].

From this foundation, three main categories of process mining techniques have been identified in the literature:

1. **Process Discovery** — the automatic derivation of a process model from event logs without relying on a priori models. This technique is fundamental for revealing the actual sequence of activities and identifying unexpected variants[15];

2. **Conformance Checking** — the comparison between a predefined process model and the behavior observed in event logs. This approach is particularly useful for detecting deviations such as skipped steps, unauthorized activity execution or violations of compliance rules [16];

3. **Process Enhancement (Improvement)** — the enrichment of existing process models with additional information, such as performance metrics, resource utilization or cost data. This enables organizations to diagnose bottlenecks, measure efficiency and guide targeted improvements [7].

Beyond methodological classification, process mining has also been increasingly integrated into process monitoring frameworks. Monitoring focuses not only on the retrospective analysis of processes but also on providing real-time or near-real-time insights into operational performance. One of the most effective ways to operationalize this monitoring is through the use of dashboards, which aggregate process indicators into accessible visual representations [8].

Dashboards act as the bridge between process mining output and managerial decision-making. They present indicators such as average case duration, resource workload or process compliance in forms that are immediately interpretable by stakeholders. Research on dashboard design for process monitoring emphasizes the importance of using appropriate visualization techniques, such as bar charts, trend lines or performance traffic lights and ensuring consistency in the use of filters and metrics [6].

In higher education and other institutional contexts, dashboards linked to process mining outputs have been shown to improve transparency and accountability, while providing decision-makers with actionable insights into administrative workflows [17]. By connecting event log analysis to interactive dashboards, organizations can move from static reporting towards continuous process monitoring, aligning operations more closely with strategic goals.

2.1.3. Data Visualization Principles for Dashboard Design

Effective visualization is the cornerstone of business intelligence (BI) dashboards, as it provides stakeholders with intuitive access to complex data. Dashboards should prioritize clarity, simplicity and contextual relevance, ensuring that users can easily interpret key performance indicators within limited screen space. Literature on dashboard design strongly emphasizes the use of bar charts, line charts, and cards due to their perceptual efficiency: bar charts allow for straightforward comparison across categories, line charts are particularly suited for tracking trends over time, and cards effectively display scalar values such as totals or averages. While pie charts may convey part-to-whole relationships, their interpretability diminishes with complexity, making them suitable only for limited use [1]. Conversely, chart types such as radial plots, polar diagrams or 3D visualizations tend to introduce unnecessary cognitive load and should generally be avoided [6].

The rise of process mining as a discipline has been strongly shaped by the tools that make these visual principles actionable. Process mining techniques, including discovery, conformance checking and enhancement, require specialized software to transform event logs into interpretable insights. Over time, two categories of tools have emerged: academic frameworks, which provide methodological breadth for research and experimentation, and commercial solutions, which focus on usability, scalability and integration into business environments.

Among academic tools, ProM is the most established framework, offering hundreds of plug-ins that cover virtually every process mining algorithm. While comprehensive, its steep learning curve limits accessibility for non-expert users. To improve reproducibility and workflow automation, RapidProM was later introduced, embedding ProM into the RapidMiner environment for repeatable analyzes [18]. More recently, PM4Py has gained prominence as a Python-based library that integrates with the broader data science ecosystem, enabling large-scale process mining experiments alongside machine learning pipelines [19].

On the commercial side, Disco has become popular for its intuitive interface and powerful log filtering capabilities, making it ideal for consultants and practitioners without deep technical expertise [20]. At the enterprise level, Celonis leads the market by extending process mining into adjacent domains such as AI-driven recommendations, automation and performance excellence programs. UiPath Process Mining and Microsoft Power Automate Process Mining connect directly to robotic process automation (RPA) environments, enabling real-time corrective action. Additionally, integrations such as the Power BI Process Mining plugin represent a growing trend towards embedding process insights directly into widely adopted BI platforms, thus bridging the gap between analytical rigor and decision-making usability.

This project is aligned with this convergence. While academic tools informed the methodological foundations, the implementation was carried out using Microsoft Power BI. This choice ensured usability and institutional alignment, while also supporting the creation of structured, KPI-driven dashboards. In doing so, the work reflects both the visualization principles of effective BI dashboard design and the practical trends in process mining, combining methodological rigor with stakeholder-oriented accessibility.

2.2. Related Work

The literature on process performance measurement and visualization is extensive and can be organized into two complementary streams. The first stream addresses the definition and selection of KPIs and the analytical techniques used to compute them from event logs, the second concerns the visualization and dashboard design needed to make those indicators actionable for stakeholders.

2.2.1. Process performance indicators and log-based performance analysis

Several studies offer structured frameworks for selecting and computing process performance indicators from event logs. Research comparing log-based performance techniques provides guidance on which metrics are most appropriate given data characteristics and analytical goals: for example, Milani & Maggi (2018) [10] evaluate a range of log-based performance analysis methods and propose criteria for selecting the appropriate analytical approach depending on the indicator (e.g., durations, throughput, variants, performance per resource). Complementary surveys in the business process domain classify indicators across dimensions such as time, cost, quality and flexibility, and show how this map to managerial needs (systematic literature reviews on business process performance measurement). Financially oriented studies stress that monetary KPIs (cost per case, waiting cost) add a relevant decision layer for prioritization and root-cause analysis [8]. These contributions collectively establish the methodological foundation used to derive KPIs from event logs and to judge their suitability for operational monitoring.

2.2.2. Visualization techniques and dashboard design

The translation of computed KPIs into usable information requires careful visualization design. Reviews of dashboard literature point to a set of established principles: prioritize clarity, minimize cognitive load, match chart type to data semantics and provide consistent global filters so users can compare indicators across the same dimensions [6]. Empirical and methodological works recommend bar charts for categorical comparisons, line charts for temporal trends and KPI cards for scalar summary values; they also warn against complex or decorative graphics (3D effects, radial plots) that impair comprehension. Research focused on process analytics further emphasizes the need to combine overview metrics (high-level KPIs) with drill-down capabilities (variants, activity-level views, resource breakdowns) so that users can move from symptom to cause within the dashboard environment (studies on process-aware dashboards and visual analytics). Financial dashboards literature complements these recommendations by showing how cost visualizations can guide managerial interventions.

2.2.3. Process monitoring in Higher Education Institutions (HEIs)

Research on process monitoring in higher education institutions shows a growing interest in applying process mining and BI to both academic and administrative workflows. One line of work demonstrates how rule-based monitoring can identify deviations in student curricula, providing early alerts for academic advisors [4]. Other studies applying predictive models to student activity logs reveal that process-oriented KPIs, such as case variants or rework frequencies, can serve as strong predictors of dropout risk.

In parallel, institutional dashboard initiatives integrate data from multiple sources to monitor quality, compliance and resource allocation [11]. These systems reveal that the combination of event logs and BI dashboards is not limited to corporate environments but has significant relevance in education, especially when monitoring operational processes like admissions, enrolments or scholarship allocations.

2.2.4. Synthesis and gap addressed by this project

The literature provides strong methodological guidance on KPI definition, log-based analysis and dashboard design. However, most HEI-related studies emphasize student-centered processes (learning analytics, course monitoring) rather than administrative workflows. Few works have implemented integrated solutions that connect directly to institutional data repositories, apply process mining for discovery and conformance and expose KPIs via BI dashboards accessible to non-experts.

This project addresses precisely that gap by focusing on document-based administrative processes, such as scholarship allocation. By combining validated KPI frameworks with practical BI dashboards, the work contributes both theoretically and practically to the underexplored area of administrative process monitoring in HEIs.

2.3. Main Challenges

Higher Education Institutions encounter significant difficulties in managing and improving their processes due to the lack of systematic measurement and monitoring mechanisms. Without reliable indicators, managers are unable to clearly see how processes are executed, which activities consume more time or where inefficiencies occur. This absence of visibility creates obstacles not only to performance evaluation but also to the identification of opportunities for optimization.

One of the main challenges lies in assessing process performance. Since execution times are rarely tracked in detail, delays or bottlenecks often remain unnoticed, preventing timely corrective action. Similarly, the frequency of different process variants and activities is not systematically analyzed, which makes it difficult to distinguish between normal practices and exceptions that may signal inefficiencies.

Resource allocation is another critical issue. Without monitoring workloads across departments and organizational units, HEIs cannot distribute human resources effectively, leading to imbalances such as staff overload in some areas and underutilization in others. The same applies to financial optimization: in the absence of cost tracking linked to process execution, it is impossible to evaluate the economic impact of idle times, waiting periods or duplicated activities.

Rework also represents a considerable hidden cost. Activities such as repeated document submissions, corrections or unnecessary approvals often remain invisible without proper monitoring, even though they consume significant time and resources.

Finally, the lack of systematic KPI tracking makes continuous improvement difficult, as decision-makers are forced to rely on fragmented information or anecdotal evidence rather than concrete data.

In summary, HEIs face the challenge of operating in the dark, without structured mechanisms for measuring and monitoring processes, it becomes extremely difficult to evaluate performance, understand resource usage, control costs, or reduce inefficiencies. This lack of transparency severely limits their ability to engage in proactive and evidence-based process optimization.

3. Methodology

This chapter describes the methodology that will guide the development of the proposed framework. It begins with the distribution of responsibilities within the project team, followed by a detailed description of the phases that compose the methodology. The final section explains the planned approach for data analysis and visualization.

3.1. Project Activities

The methodological approach adopted in this project followed a structured sequence of activities, designed to ensure that the developed dashboards responded both to academic requirements and to institutional needs regarding process monitoring. The methodology can be summarized in five main stages, which are outlined in Figure 2 and later represented schematically for clarity. The tasks within these stages were distributed between the two project contributors, ensuring both collaboration and specialization according to expertise.

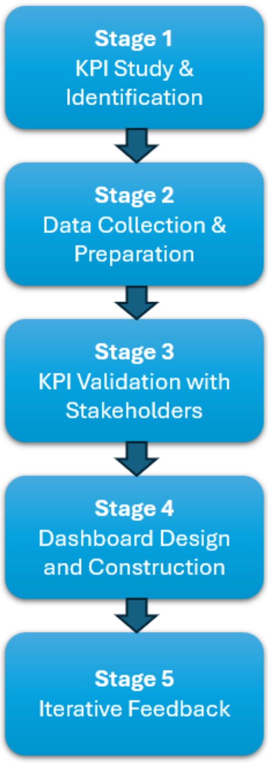

Figure 2- Methodological Framework

The first stage focused on the study and identification of performance indicators. I carried out a comprehensive literature review to identify metrics that were both theoretically grounded and relevant to the processes. In parallel, Bruno Silva conducted an exploratory analysis of the institution's practices and existing tools, allowing us to compare academic perspectives with operational realities. The outcome of this joint effort was a preliminary list of candidate KPIs, validated through alignment between academic research and institutional requirements.

The second stage concentrated on data collection and the application of Process Mining techniques. This stage was carried out collaboratively: Bruno Silva was primarily responsible for extracting event logs from the institution’s management information systems, ensuring data completeness and accessibility, assessing data quality, identifying missing or inconsistent entries and preparing the cleaned dataset for analysis. Together, we selected and adapted appropriate Process Mining techniques to enable the calculation of KPIs, with particular emphasis on process durations, bottlenecks and deviations from expected flows.

The third stage involved the validation of KPIs with institutional stakeholders. I led the preparation of presenting materials for the interactive session with stakeholders, during which the proposed indicators were explained and discussed. And by developing a survey instrument to collect structured feedback on the clarity, usefulness and relevance of each KPI. This participatory step ensured that the indicators selected for implementation were not only academically sound but also meaningful and accepted in the institution’s day-to-day context.

The fourth stage focused on the study of visualization approaches and the construction of dashboards. I analyzed visualization options, comparing charts, cards and process maps in terms of clarity and interpretability, and then designed the initial dashboard prototypes. Bruno Silva supported the technical implementation, particularly in configuring navigation and filtering mechanisms to ensure consistency across dashboards. Three complementary dashboards were implemented: one dedicated to operational KPIs, one estimating financial impact and the last presenting process execution through maps. This stage combined design and technical development, with both contributors working iteratively to refine the visual outputs.

Finally, the fifth stage was dedicated to refinement through iterative feedback. The dashboards were presented to institutional stakeholders and collected feedback.

In summary, this methodological framework was structured, collaborative and iterative. It combined theoretical foundations, technical implementation and participatory validation, while distributing tasks strategically between the two contributors. This ensured not only methodological rigor but also practical alignment with institutional needs. A schematic representation of these five stages is provided in Figure 2, serving as a visual guide to the methodological process before each stage is described in detail.

3.2. Survey

As part of the process of validating the KPIs selected for inclusion in the dashboards, a structured internal consultation was conducted with institutional stakeholders. To facilitate this engagement, a PowerPoint presentation was developed, outlining a set of proposed KPIs relevant to document-based processes. Each indicator was accompanied by its conceptual definition and visual examples of how it could be represented using dashboard tools.

The visualization examples were drawn from a diverse range of recognized platforms, including Microsoft Power Automate, Disco, PMTK, Celonis, QPR, Power BI, and Tableau. This variety ensured that participants were exposed to established practices in data representation and encouraged informed feedback on both content and usability dimensions.

The presentation was delivered during an internal training session entitled Process Management Training for Staff, organized by the central services of the Polytechnic University of Leiria. A total of 38 internal staff members, many of whom work directly with or in proximity to the analyzed processes, participated in the session. These participants were asked to evaluate the relevance of each KPI based on their professional experience and operational familiarity with the institutional workflows.

For the evaluation, each participant was invited to assign a score ranging from 1 (not relevant) to 5 (highly relevant) to each KPI. The goal of this exercise was to prioritize indicators that would provide the most meaningful insights for process monitoring and improvement. The results of the evaluation revealed a high degree of consensus, with all selected indicators receiving average scores above 4.0, thereby confirming their perceived value and applicability. This feedback was instrumental in shaping the final selection of indicators implemented in the dashboards.

By involving end users early in the design process, the project ensured a degree of participatory validation, aligning analytical outputs with real organizational needs and promoting adoption of the developed tools.

3.3. Dashboard Development Method

The execution of this work will follow a structured methodology, organized into sequential phases that will ensure both methodological rigor and practical applicability. Each phase will be carefully designed to build upon the previous one, guaranteeing that the outcome is coherent, consistent and aligned with the project’s objectives.

The approach will begin with the preparation of data. Event logs will be collected from the selected information system and the raw data will be processed to ensure accuracy, completeness and usability. This preparation will involve several steps: data extraction, cleansing of inconsistencies, transformation into a standardized format and enrichment with additional attributes when necessary. The goal of this stage will be to produce an event log dataset that meets the requirements of process mining techniques while maintaining the integrity of the original information.

Once the data preparation is completed, the project will proceed to the definition of performance indicators. These indicators will be grounded in the literature while also reflecting the specific needs of the case study. Each indicator will be explicitly defined in terms of:

- its conceptual meaning;
- the process data required for its calculation;
- the mathematical or logical formula used to compute it;
- the updating mechanism to ensure that it remains current;
- and the intended visualization format.

By following this structured definition, the indicators will provide a transparent and replicable way of measuring process performance.

The third phase will consist of the design of dashboards. These dashboards will be developed with the dual purpose of providing an intuitive visualization for end users while also supporting in-depth exploration of the data. The dashboards will include filters, comparative charts, and drill-down functionalities, enabling users to view performance both at a global process level and at the level of individual cases, activities, or resources. The design will prioritize clarity and usability, ensuring that decision-makers can quickly identify trends, inefficiencies, and opportunities for improvement.

Following the design, the implementation phase will take place. This will involve translating the conceptual design into an operational system using appropriate business intelligence and data visualization tools. During this stage, the data will be connected to the visualization environment, the DAX measures for the indicators will be implemented and interactive elements such as slicers and filters will be configured. The implementation will also include technical validation steps to confirm that each indicator behaves as expected and that the dashboards function correctly under different usage scenarios.

Finally, the methodology will include an evaluation and validation phase. The proposed framework will be applied to the case study dataset and the results will be assessed with respect to accuracy, completeness and practical utility. This validation will not only check whether the dashboards correctly represent the underlying data but also whether they provide added value for analysis and decision-making. Feedback from stakeholders will be sought whenever possible, in order to strengthen the practical relevance of the work.

Throughout all phases, the focus will remain on ensuring reproducibility and scalability. The methodology will be documented in detail so that it can be reapplied to other processes and adapted to different organizational contexts. The expectation is that this structured and future-oriented approach will lead to a framework that is both academically rigorous and practically impactful.

4. Requirements and Dashboard Architecture

This chapter outlines the visualization strategy, survey results, functional and non-functional requirements defined for the implementation of the dashboard solution, followed by a description of the general system architecture and the technologies employed in its development. The design of the solution aimed to ensure usability, scalability, and alignment with institutional constraints and tools.

4.1. KPI Selection and Survey Results

To determine which metrics should be incorporated into the dashboards, a preliminary research and validation phase was conducted. The objective was to identify indicators that would be most relevant for monitoring institutional processes while ensuring that they aligned with the informational needs of stakeholders.

As part of this phase, an internal training session titled “Process Management Training for Staff” was organized. During the session, a wide range of potential KPIs was introduced through a PowerPoint presentation (Appendix A). The presentation included conceptual definitions of the indicators, their intended purpose and examples of visual representation. The examples were sourced from several established process mining and business intelligence platforms, including Microsoft Power Automate, Disco, PMTK, Celonis, QPR, Power BI and Tableau, to illustrate best practices in process monitoring and visualization.

The KPIs proposed for validation spanned multiple perspectives of process analysis. These included:

- Time indicators, such as average, minimum, maximum and median case completion times, designed to assess process efficiency and highlight outliers;
- Case and variant indicators, such as the total number of cases, number of process variants, duration per variant and frequency per variant, which together provide insight into workload, process complexity and variability;
- Activity indicators, including the total number of activities and their distribution over time, reflecting the complexity and workload of the process;
- Compliance and quality indicators, such as rework frequency and performance deviations, aimed at assessing adherence to expected workflows and identifying inefficiencies.

To ensure comparability across dashboards, all indicators were designed to support a common set of filters. Users would be able to refine their analysis by year, organizational unit (OU), and process participant and in some cases by case status or activity type. This filtering framework ensured consistent interaction across the entire dashboard solution.

Following the presentation, a survey was distributed to 38 institutional staff members, many of whom are directly involved in administrative and process-related activities. Participants were asked to evaluate each KPI using a five-point scale (1 = not relevant, 5 = highly relevant). The aim was to measure how well each indicator matched the stakeholders' informational needs and its potential contribution to process transparency and decision-making.

The feedback received was highly positive, with all proposed KPIs receiving average ratings above 4.0 (Appendix B). This indicates strong alignment between the selected metrics and the practical expectations of users. The average scores for each KPI are presented below:

- Total number of cases: 4.34;
- Number of variants: 4.18;
- Duration per variant: 4.08;
- Frequency per variant: 4.26;
- Number of activities: 4.13;
- Case completion time: 4.11;
- Average case time: 4.03;
- Performance analysis: 4.24;
- Rework Frequency/Percentage: 4.45;
- Frequency Analysis: 4.21;
- Activity Level over Time: 4.11.

The high evaluation scores provided clear evidence of the relevance and utility of the selected indicators. Additionally, informal qualitative feedback gathered during the session revealed that participants appreciated the clarity of the visualizations and the ability to filter data according to specific organizational dimensions, such as organizational unit, process participant and time-span period.

This participatory approach to validation not only enhanced the credibility of the dashboard design but also fostered a sense of ownership among stakeholders. By incorporating their feedback into the final development cycle, the dashboards were further refined to better reflect the needs and expectations of their intended users.

4.2. Data Workflow and Visualization Strategy

At the initial stages of the project, Microsoft Power Automate was considered as a strategic tool for automating dashboard generation and streamlining data workflows. Power Automate is a cloud-based service that enables task automation, process orchestration and the integration of disparate systems using Robotic Process Automation (RPA) and artificial intelligence (AI). Within the Microsoft Power Platform ecosystem, it provides robust capabilities for process mining, real-time monitoring and scalable automation, making it particularly effective for enhancing digital transformation initiatives.

However, due to licensing limitations, specifically, the unavailability of a Power Automate Premium license, it was not feasible to access advanced features such as process mining, premium connectors, desktop flows or AI-driven automation tools. Although the free trial version temporarily granted access to these functionalities, its expiration would have rendered several automated flows inoperable unless it was upgraded to a paid license.

As a result, the project's technical strategy was revised to focus on manual dashboard development using Microsoft Power BI, a business intelligence platform that enables the connection, modelling and visualization of data through interactive and dynamic dashboards.

This approach, while requiring more direct effort, offered greater flexibility and customization in data modelling, filtering and visual presentation. Furthermore, Power BI's robust features enabled the construction of modular, dynamic dashboards capable of supporting multiple process types with user-friendly interactivity.

The transition to Power BI ensured alignment with institutional tools already in use, while maintaining the ability to scale and adapt to future data integration and automation opportunities.

In collaboration with Bruno Vieira Silva, we were responsible for preparing and transforming the raw datasets provided by the PUL. These datasets, representing various internal processes, were first loaded into a centralized data warehouse, specifically designed to support structured storage, preprocessing and efficient querying.

Once ingested, the student Bruno performs a detailed exploratory data analysis (EDA) to assess the quality and usability of each data element. This includes identifying missing values, inconsistencies, redundancies and structural anomalies. Particular attention is paid to records that are rendered unusable due to data quality issues, often stemming from incorrect or incomplete data collection practices at the source. As a result of this evaluation, non-viable data is excluded from further processing.

Following the assessment phase, we carried out data cleaning and transformation procedures. These include standardizing formats, correcting data types, resolving inconsistencies and restructuring tables to enable coherent integration. The objective is to ensure that the datasets meet the necessary quality standards for reliable analysis and visualization.

After the transformation is complete, the curated data warehouse is connected to Microsoft Power BI, which serves as the front-end tool for visualization. This connection allows the dashboards developed in this project to access clean, reliable and query-optimized datasets, thereby ensuring the integrity of the visualized insights.

This collaborative approach not only ensured a clear separation of concerns, between data engineering and data visualization, but also promoted methodological rigor, enabling each phase of the project to be executed with focus and expertise

4.3. Main Functional Requirements

The dashboard system was designed to fulfill several essential functional requirements, ensuring it could support both analytical needs and user interaction expectations. The key functional requirements identified are as follows:

1. **Visualization of Internal Process KPIs:** The system must present key performance indicators that reflect the behavior, frequency and performance of internal processes recorded in several information systems. These KPIs should be displayed in a clear, dynamic and interactive manner.

2. **User Filtering Capabilities:** Users should be able to apply filters to explore the data based on relevant dimensions. Specifically, filtering by process type, year, organizational unit and process participant must be supported to allow customized analysis.

3. **Navigation Between Dashboards:** The solution must support intuitive navigation across multiple dashboards. A main interface should enable users to select the dashboard of interest and be redirected to the corresponding analytical view, facilitating seamless exploration of various process scenarios.

4.4. Non-functional Requirements

Beyond core functionality, the process dashboard monitoring platform must adhere to a set of non-functional requirements that ensure the solution is user-friendly, sustainable and aligned with institutional standards. The key non-functional requirements include:

- **High Usability and Intuitive Navigation:** The dashboards must be designed with end users in mind, providing intuitive controls, clearly labelled filters and consistent visual layout to reduce cognitive load and training requirements.
- **Visual Consistency Across Dashboards:** A uniform design language and layout style should be applied to all dashboards to ensure visual coherence, regardless of the process or metric being analyzed. This consistency supports better interpretation and minimizes confusion.
- **Compatibility with Institutional Tools:** The system must be fully compatible with technologies supported by the institution, particularly Microsoft Power BI.
- **Performance and Responsiveness:** The dashboards must be optimized to handle multiple filters and moderate volumes of data without compromising performance. Load times and data refresh should remain within acceptable limits for routine use.
- **Modular and Scalable Structure:** The architecture should allow for the addition of new processes or indicators in the future without requiring significant redesign. This modularity supports long-term sustainability and adaptability of the solution.

4.5. General Architecture

The overall architecture of the solution was designed to ensure both analytical depth and ease of use. At its core, the system is organized into three complementary layers that work together to transform raw institutional data into meaningful insights.

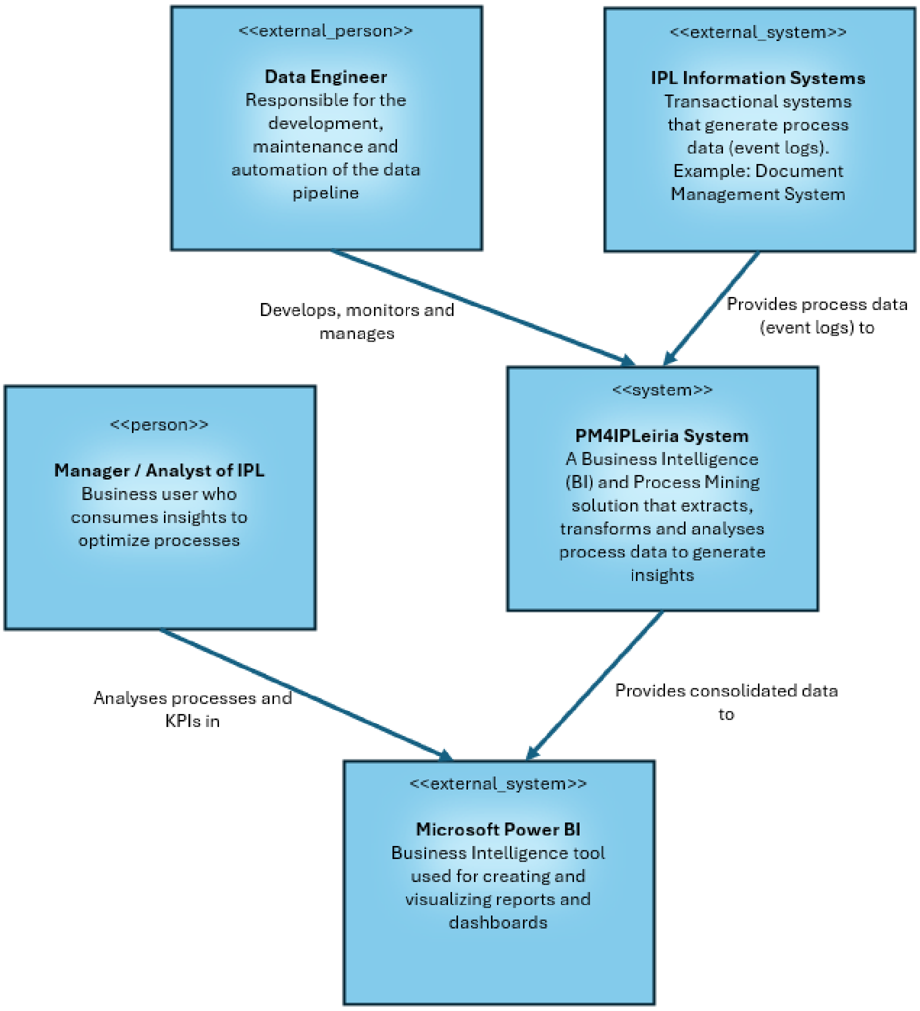

Figure 3 - System Context Diagram for the PM4IPLeiria Solution

The PM4IPLeiria solution was designed as an integrated architecture that connects institutional data sources, data processing workflows and business intelligence visualization tools. Its structure is represented in the System Context Diagram, which illustrates the interactions between the central system and surrounding actors, external systems, and end-users.

At the core of the solution lies the PM4IPLeiria System, a business intelligence and process mining platform designed to extract, transform, and analyze process data to generate actionable insights. The system interacts with four main entities. The institution's information systems, such as the Document Management System, provide the raw event logs and transactional records that form the foundation for monitoring. The Data Engineer maintains the technical backbone of the data pipeline, ensuring that extraction, cleaning, and transformation procedures are carried out consistently. In this project, that role was performed by Bruno Vieira Silva, who was responsible for consolidating heterogeneous datasets into a centralized data warehouse, creating a reliable and query-optimized structure to support analysis.

Building on this foundation, the data processing layer transforms raw records into meaningful performance indicators. Key dimensions such as time, resources and costs are derived from the data warehouse, enabling the calculation of process durations, identification of bottlenecks, detection of deviations and estimation of costs. These performance metrics form the analytical basis of the solution and ensure that subsequent visualizations are supported by consistent, validated data.

At the top of the architecture is the visualization layer, implemented through Microsoft Power BI. This layer makes the results accessible to institutional users through interactive dashboards, which include views tailored to specific perspectives: a navigation interface, a KPI dashboard focused on performance monitoring, a financial dashboard for cost and resource analysis and a process flow map dashboard highlighting frequency and timing of activities. These dashboards were designed and implemented as part of this project, ensuring that technical outputs were translated into clear, usable and interactive insights for stakeholders at PUL.

By structuring the architecture into distinct but interdependent layers, data integration, data processing and visualization, the PM4IPLeiria solution ensures both methodological clarity and scalability. Data is ingested from transactional systems, maintained by the Data Engineer, transformed into KPIs through process mining techniques and delivered to decision-makers via dashboards. This layered design not only facilitates transparency in current processes but also establishes a solid foundation for extending the solution to additional workflows and institutional contexts in the future.

4.6. Technology Stack

The implementation of the PM4IPLeiria solution combined several technologies, each aligned with the components represented in the context diagram and reflected a clear division of responsibilities between the two students.

For the Data Engineer block, my colleague Bruno Vieira Silva was responsible for building the backend infrastructure. He used Azure Data Factory, Azure SQL Database, Python (PM4Py, Pandas), and Docker to extract, transform and consolidate data from heterogeneous sources. His work resulted in a centralized data warehouse that served as the backbone of the solution, ensuring that fragmented institutional datasets were harmonized and made reliable for analysis.

For the PUL Information Systems block, the institution’s Document Management System provided the main source of event logs. These raw records were integrated into the data warehouse as part of Bruno’s preprocessing and data preparation tasks.

For the PM4IPLeiria System block, the consolidated data was transformed into meaningful performance indicators. This analytical layer was the bridge between backend preparation and dashboard design, ensuring that metrics such as time, costs and rework could be systematically evaluated.

For the Microsoft Power BI block, I was responsible for designing and implementing the dashboards. Using Power BI, I modelled the prepared data, defined KPI visualizations and created interactive dashboards covering process performance, financial analysis and process flow perspectives. Power Automate was also explored at an early stage to test automated flows, though its use remained limited.

Finally, for the Manager/Analyst block, institutional stakeholders accessed the dashboards through the Power BI service, where they could interact with KPIs, filters and visual elements to support evidence-based decision-making.

By distributing the technologies across these blocks and dividing responsibilities between data engineering and visualization, the project ensured a robust backend for data preparation and a user-friendly interface for analysis. This collaborative approach allowed the PM4IPLeiria solution to combine technical reliability with practical usability.

5. Dashboard Implementation

This chapter presents the implementation of the dashboards that constitute the core of the process monitoring solution. Building on the methodological framework and architectural design defined in the previous chapters, the focus here is on transforming the validated KPIs and processed data into interactive visual tools.

5.1. Process time and control-flow dashboard

To determine which metrics should be visualized, a preliminary research phase was conducted, complemented by stakeholder input collected through the survey described in Chapter 4.

Based on the survey, the process time and control-flow dashboard will contain the following KPIs:

- The average case duration: Mean duration required to complete cases, calculated based on the total number of completed cases;
- The maximum case duration: The longest duration recorded for the resolution of a case, measured from its opening to its completion;
- The minimum case duration: The shortest duration recorded for the resolution of a case, measured from its opening to its completion;
- The median case duration: The value that separates the faster half from the slower half of case resolution times, indicating a typical completion time;

Figure 4- Time Indicators

- The total number of activities corresponds to all distinct activities executed within the process;
- The total number of variants refers to the number of different sequences that a case can follow during its process, depending on the decisions and events at each stage. This number varies according to the complexity of the process;
- The total number of cases in a system corresponds to the overall count of case records, including both completed and ongoing cases;

Figure 5- Total of Activity, Variant and Cases Cards

- The duration per case corresponds to the specific duration between the opening and completion of an individual case;
- The average duration of each variant is the average time required to complete a case by following a specific sequence of steps and decisions;
- The frequency of each variant is the number of times a particular process sequence occurs within the total set of analyzed cases.

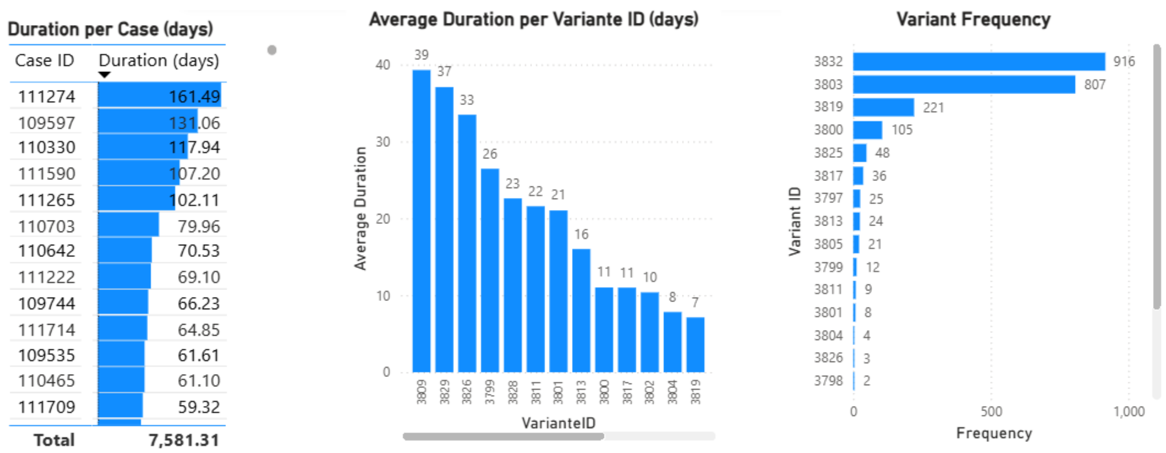

Figure 6- Graphs of Case and Variant Indicators

To ensure consistency and comparability, all dashboards share a common set of global filters: year, organizational unit and process participant. These filters allow users to narrow the analysis and maintain a coherent perspective across the different indicator groups.

5.2. Financial Dashboard

The internal process databases provided by the Polytechnic University of Leiria did not include direct financial information regarding process costs. Therefore, cost estimates used in this project were defined in collaboration with institutional stakeholders and validated through their expert input. These values, while not extracted from the original datasets, are grounded in realistic approximations and were adopted to enable meaningful economic analysis within the developed dashboards.

The financial indicators incorporated into the economic dashboard include:

- Execution Cost: Represents the monetary cost associated with the active processing time of a case, calculated by multiplying execution time by a fixed hourly rate;

- Waiting Cost: Refers to the cost incurred during periods when a case is inactive or pending, calculated using a reduced hourly rate (excluding material usage);
- Human Resources (HR) Cost: Reflects the labor cost based on the total time a case remains open, using a standard hourly wage rate for personnel involved;
- Infrastructure Cost: Accounts for the expenses related to physical infrastructure (e.g., office space, utilities) allocated over the total time the process is active;
- Material Cost: Represents the estimated consumption of physical materials during process execution;
- Equipment Cost: Includes the depreciation or operational cost of equipment used throughout the process duration;
- Software Cost: Covers licensing, maintenance, and operational use of software tools employed in the execution of the process;
- Total Process Cost: The aggregate of all individual costs (execution, waiting, HR, infrastructure, material, equipment, and software) associated with the entire process;
- Average Case Cost: The mean cost per case, calculated by dividing the total process cost by the number of cases;
- Cost per Case: The cost associated with each individual case, derived by summing the costs of all activities that comprise that case;
- Average Cost per Activity: The average cost for executing a single activity, obtained by dividing the total process cost by the number of activities performed.

Economic indicators calculated from estimated costs:

- Execution cost = Execution time (hours) × €18.33;
- Wait cost = Wait time (hours) × €17.14;
- HR cost = Total time (hours) × €11.28;
- Infrastructure = Total time (hours) × €3.02;
- Software = Total time (hours) × €1.35;
- Equipment = Total time (hours) × €1.49;
- Total and average costs per activity/case/process.

The economic dashboard incorporates filters such as Year, Process Participant and Organizational Unit, which are applied uniformly across all financial indicators.

5.3. Process Map Dashboard

The Process Map dashboard contains two process mining visualizations (Figure 7). The first map illustrates the frequency of transitions between activities, indicating how many cases move from one activity to the next. The second map represents performance by showing the average duration it takes for a case to transition from one activity to the next.

A single filter is available on this dashboard, allowing users to select the specific process they wish to analyze. Both maps update dynamically based on the selected process.

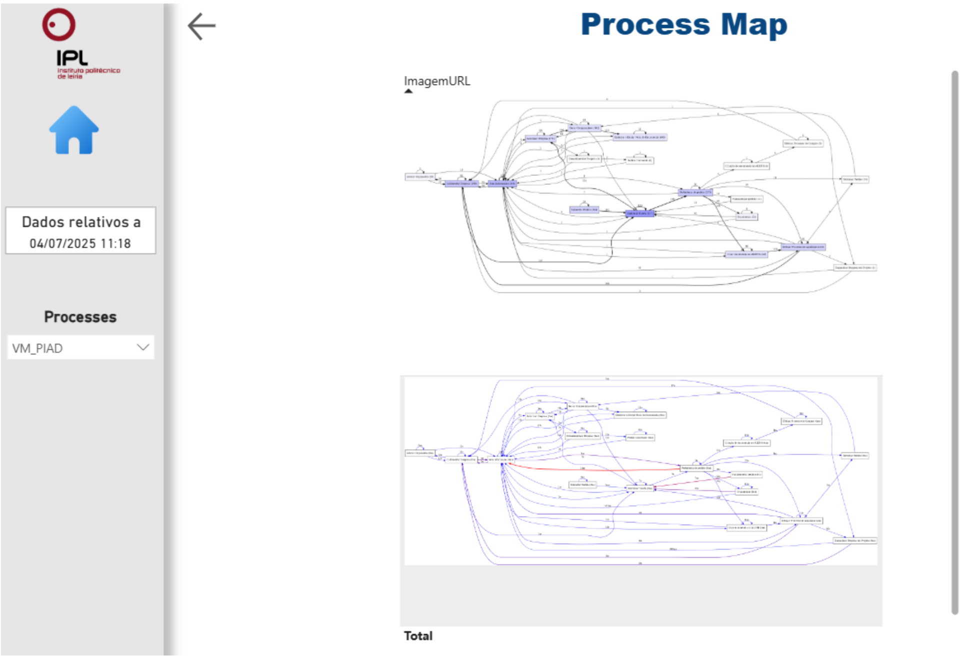

Figure 7- Process Map dashboard

5.4. Dashboard Descriptions

The visualization component of the project is composed of three distinct dashboards developed in Microsoft Power BI, each designed to address different process perspectives dimensions: time operational performance, economic cost estimation, and process flow representation. These dashboards serve as the central interface through which users interact with and explore the data. The following sections describe the layout, functionality, and content of each dashboard.

5.4.1. KPI Dashboard

The KPI Dashboard offers a comprehensive overview of process performance metrics through a clear and interactive interface. It includes several navigation buttons with distinct purposes. A “Home” button is provided to return to the main navigation page, where users can select which dashboard they wish to view. Additionally, located in the upper-right corner of the title area is a button that links directly to the Financial Dashboard, allowing seamless forward navigation.

On the left-hand side of the interface, a panel displays the filters that can be applied to the visualized data. The first and most critical filter enables users to select the specific process they wish to analyze. Beneath it are three additional filters, Year, Process Participant and Organizational Unit, which refine the data view based on temporal and organizational dimensions.

The dashboard layout includes seven KPI cards and three bar charts. The KPI cards display key summary metrics:

- Average case duration per day;
- Maximum, minimum, and median case durations;
- Total number of activities associated with the process;
- Total number of process variants;
- Total number of cases recorded for the process.

Beneath these summary indicators, three bar charts provide more detailed insights:

1. Duration (in days) for each individual case;
2. Average duration (in days) per variant;
3. Frequency of occurrence for each variant.

This dashboard enables users to explore trends and patterns across different processes and organizational contexts, with a high degree of flexibility and clarity.

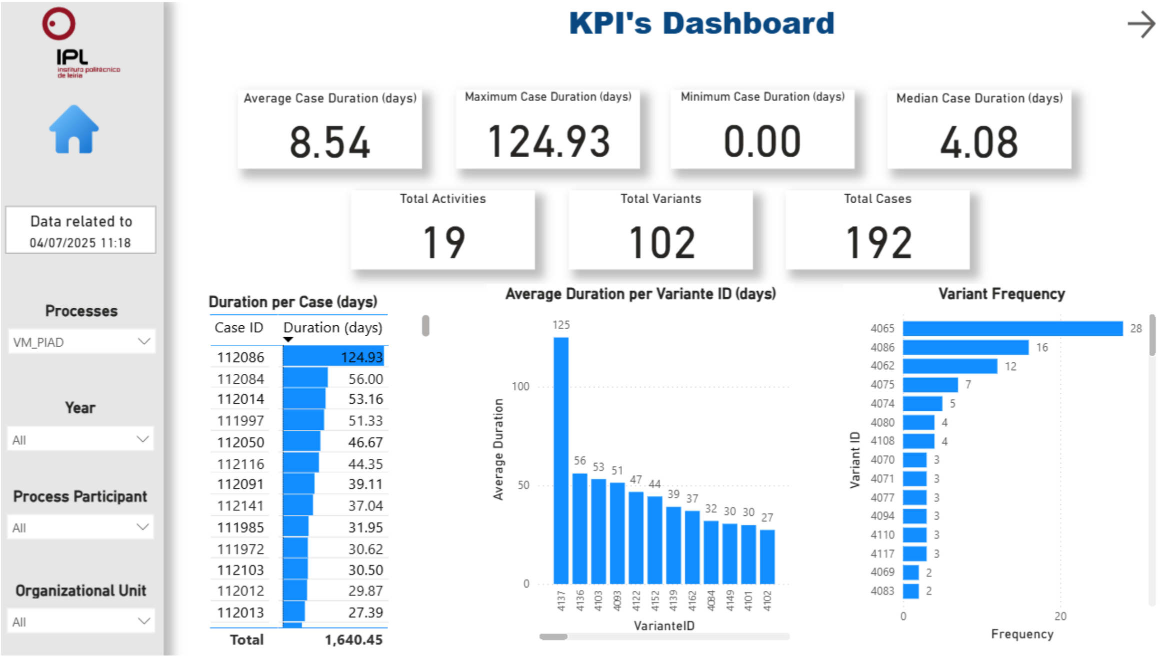

Figure 8- KPI Dashboard

5.4.2. Financial Dashboard

The Financial Dashboard maintains the same navigation and filter structure as the KPI Dashboard, ensuring consistency across interfaces. However, an additional button appears to the left of the title, enabling users to navigate back to the previous dashboard page, thus facilitating bidirectional movement between visual reports.

The filters, Year, Process Participant, Organizational Unit and Process Selection, are retained, allowing users to conduct focused economic analyzes on the selected process.

This dashboard presents eight KPI cards and two bar charts. The KPI cards summarize key financial indicators, including:

- Average execution cost;
- Average waiting cost;
- Human resource cost;
- Infrastructure cost;
- Software cost;
- Equipment cost;
- Total cost of the process;
- Average cost per case.

The two bar charts provide:

1. A breakdown of total cost per case;
2. The average cost associated with each activity.

This economic analysis supports more informed resource allocation and cost management decisions within the organization.

The use of average values for the cost-related KPIs ensures that the financial performance of processes is presented in a normalized and comparable way. Instead of reflecting only the total volume of cases, which could vary significantly across time periods or organizational units, averages highlight the typical cost required to complete a single case. This approach enables fairer comparisons across processes and variants, isolates inefficiencies more effectively and offers a clearer perspective on the expected resource consumption per case, independent of workload fluctuations.

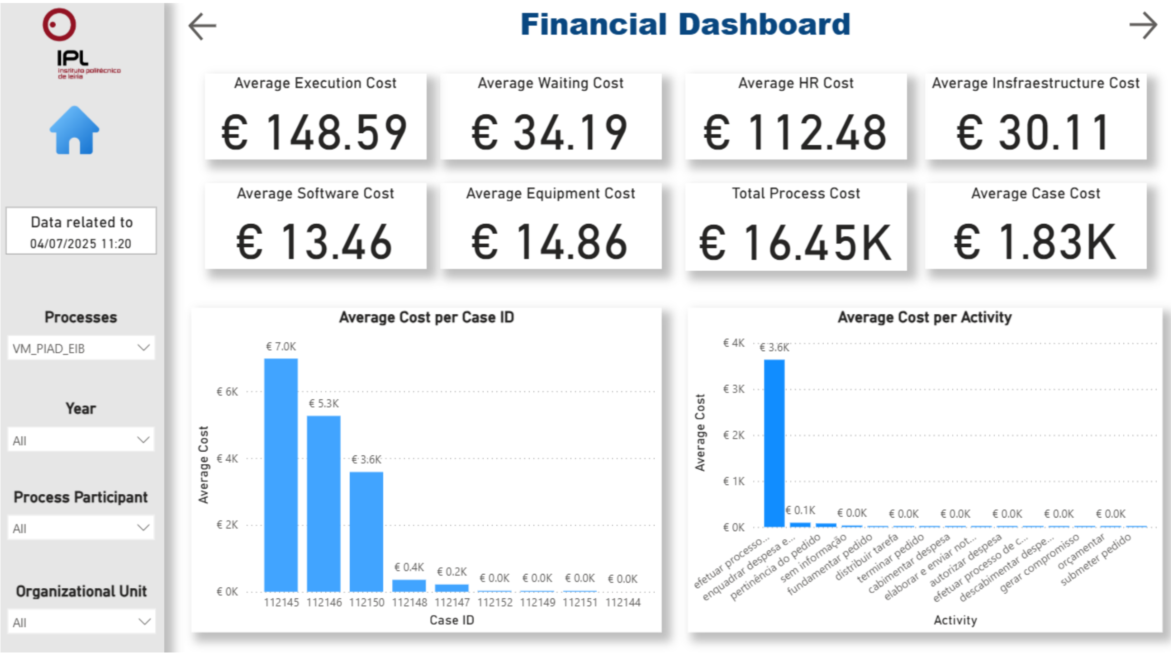

Figure 9- Financial Dashboard

5.4.3. Process Map Dashboard

The Process Map Dashboard has a more simplified structure, focusing solely on visualizing the sequence and performance of process flows. Navigation is limited to a “Home” button and a “Back” button that returns the user to the previous dashboard.

Unlike the other dashboards, this view includes only a single filter, the process selector, allowing users to switch between process visualizations without additional filtering dimensions.

The dashboard includes a dedicated card that displays the percentage of cases in which rework occurred, providing a clear overview of process inefficiencies.

The dashboard also consists of two static process maps, represented in image format:

- The upper map illustrates the frequency of transitions between activities, highlighting how often each step is followed by a specific subsequent activity (i.e., flow frequency);
- The lower map focuses on temporal performance, showing the average duration between each activity transition, thus providing insights into process delays and bottlenecks.

These visualizations, although less interactive, offer an intuitive overview of structural and time-based characteristics of each process, complementing the quantitative views provided by the other dashboards.

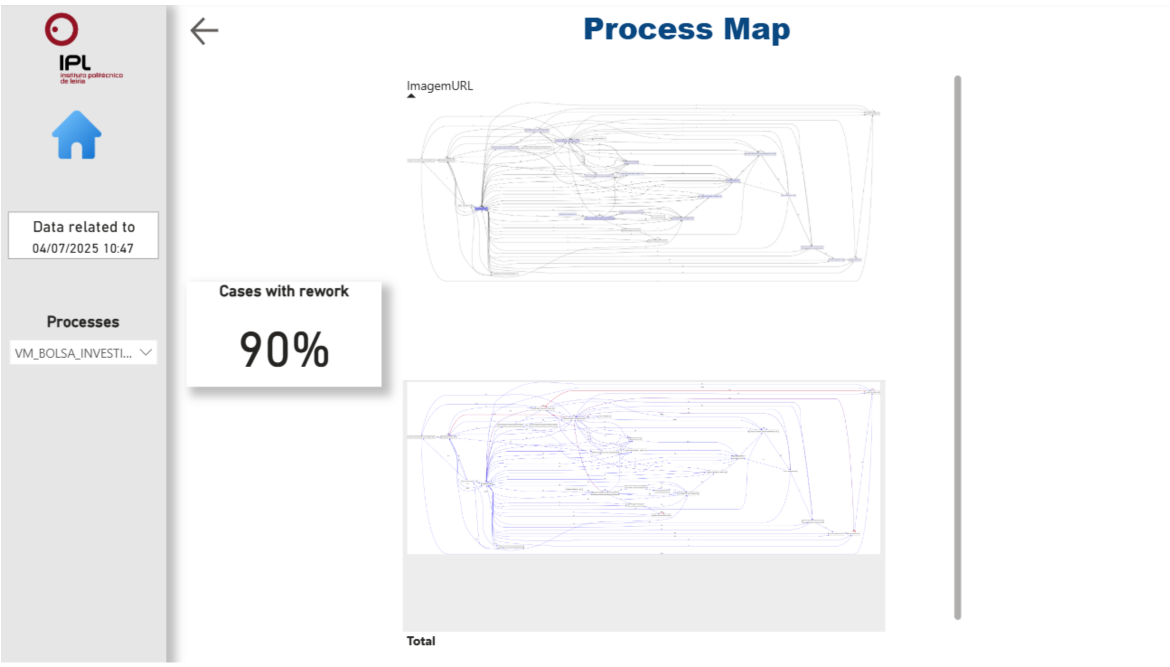

Figure 10- Process Map Dashboard

5.5. Limitations in KPI Implementation

Despite being highly rated by stakeholders during the validation phase, one key performance indicator, Activity Level over Time, could not be implemented in the final dashboard due to limitations in the structure and quality of the available data.

The Activity Level over Time indicator, which seeks to quantify the number of activities performed within specified time intervals (e.g., daily, weekly, monthly), depends on consistently recorded execution timestamps for each activity. The partial and inconsistent nature of the time-related fields across different processes rendered this type of temporal analysis infeasible.

6. Validation and Testing

6.1. Functional Testing

Functional testing was conducted to verify that all components of the dashboards operated in accordance with their intended design. The primary objective of this testing phase was to ensure that the interactive elements, including navigation buttons, slicers and filters, responded correctly to user inputs, and that the visualizations displayed accurate and consistent data representations.

Each dashboard page was systematically tested to confirm that filter selections (such as year, organizational unit and process participant) dynamically updated all associated visual elements. Navigation buttons were evaluated to ensure proper redirection between pages and appropriate loading of the selected process context. Particular attention was given to verifying that no discrepancies occurred when switching between filters or processes, and that all KPIs refreshed correctly in response to user interaction.

Special consideration was also given to edge cases, such as empty or incomplete records, to ensure that the dashboards handled missing data gracefully without errors or misleading visual output. In such scenarios, Blank values were displayed, preserving the clarity and interpretability of the information.

The successful completion of functional testing confirmed that the dashboards were technically sound, fully interactive and aligned with the analytical logic of the project. These results assured that end users would be able to navigate and interpret the dashboards without encountering usability issues or inconsistencies in the presented data.

Functional testing was carried out to ensure that the dashboards developed for monitoring the scholarship allocation process performed as expected. The primary objective was to validate that navigation, filters, KPIs, and process visualizations behaved consistently and provided meaningful insights for decision-makers. Figures 13 to 21 present the key outcomes of this validation.

Figure 11- Navigation Page

Figure 11 illustrates the entry page of the dashboard solution, where users can select the dashboard that they want to analyze. The functional tests confirmed that navigation buttons redirected correctly to the KPI, Financial and Process Map dashboards, ensuring intuitive exploration.

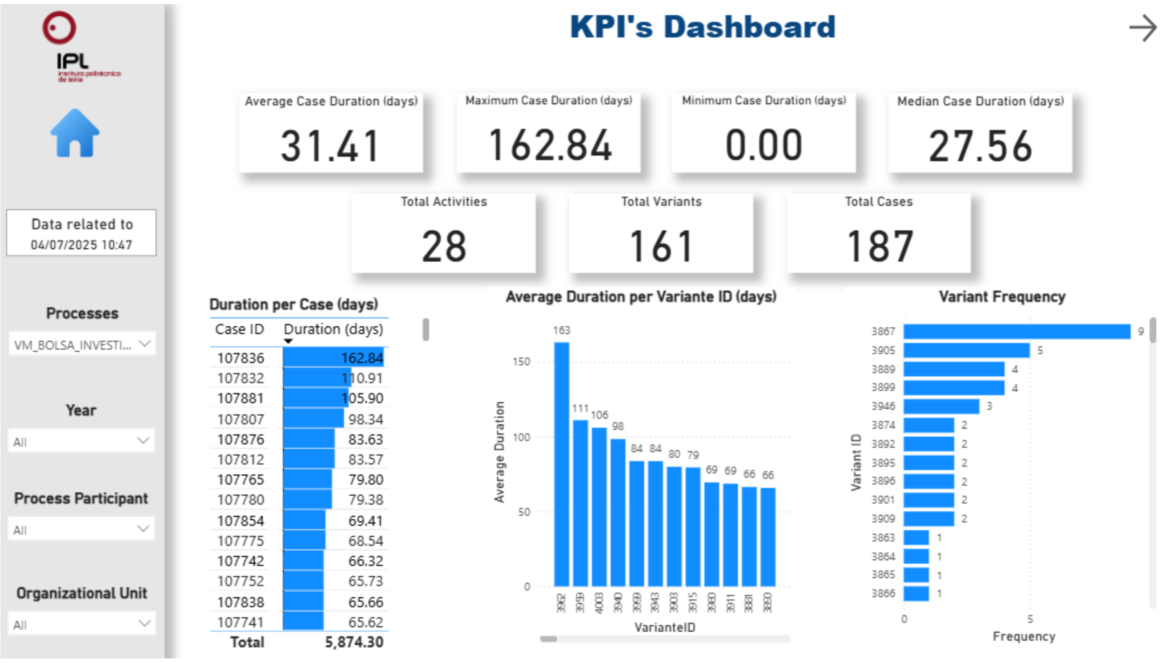

Figure 12- KPI Dashboard (without filters)

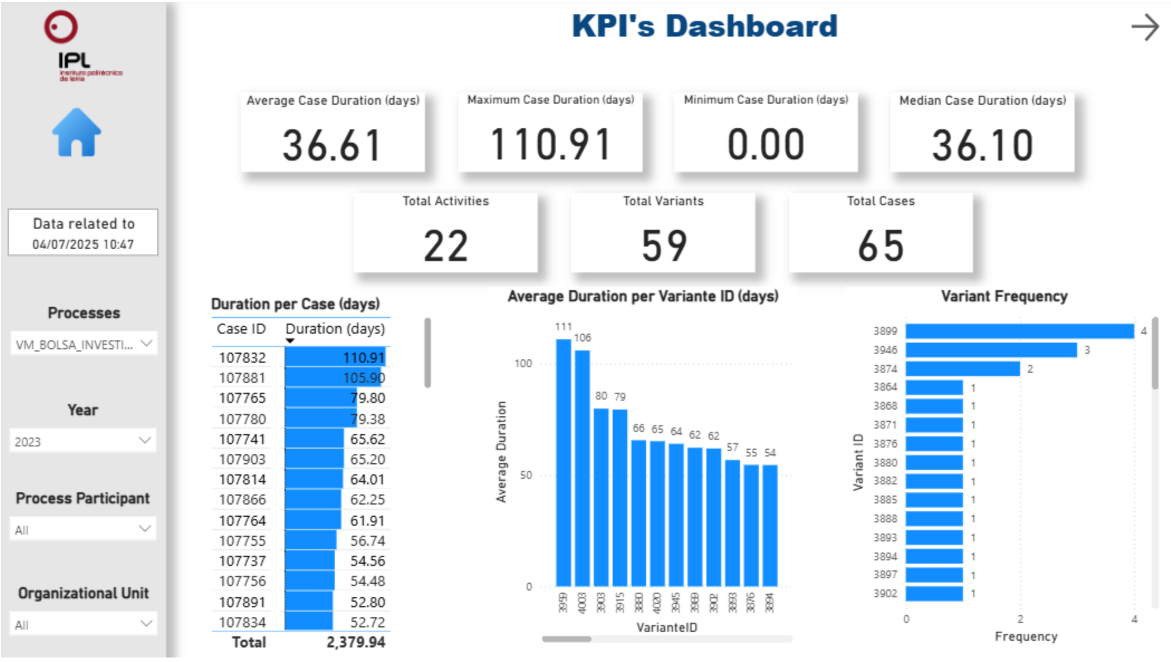

Figure 13- KPI Dashboard (filtered by Year)

Figures 12 and 13 demonstrate the KPI Dashboard for the scholarship allocation process. Figure 12 shows the dashboard without filters, presenting an overview of all recorded cases. Figure 13 applies a filter by Year and all KPIs and charts update dynamically to reflect only the selected year. This confirmed that the dashboards adapt well to broader filters but may show limited variation when the case volume is small.

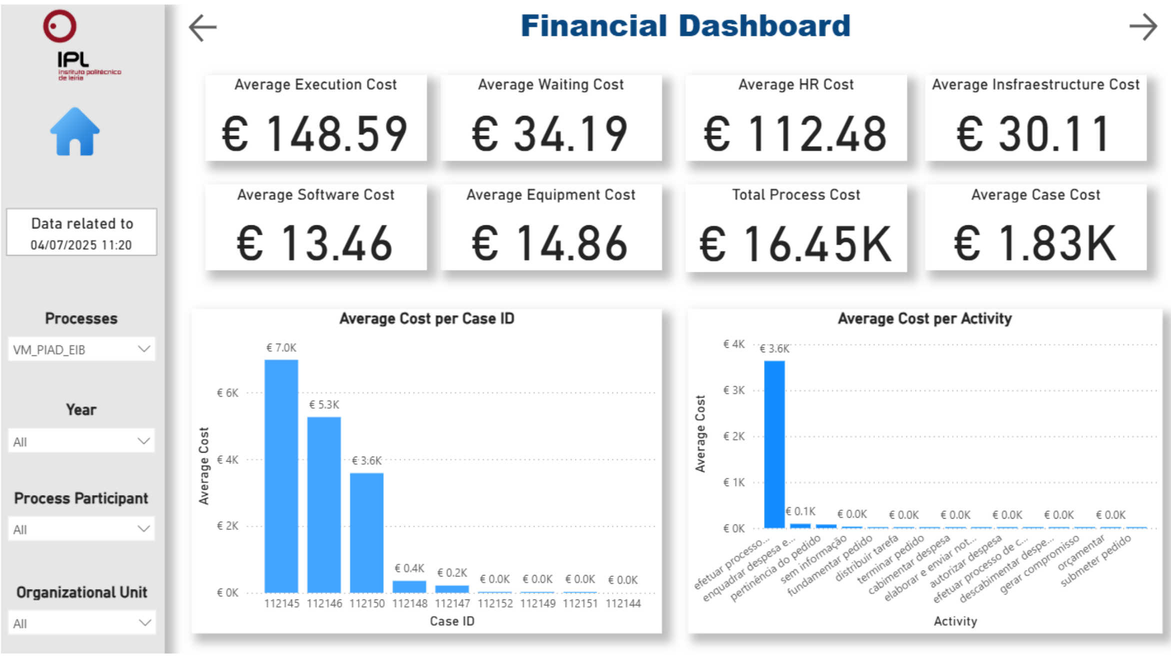

Figure 14- Financial Dashboard (without filters)

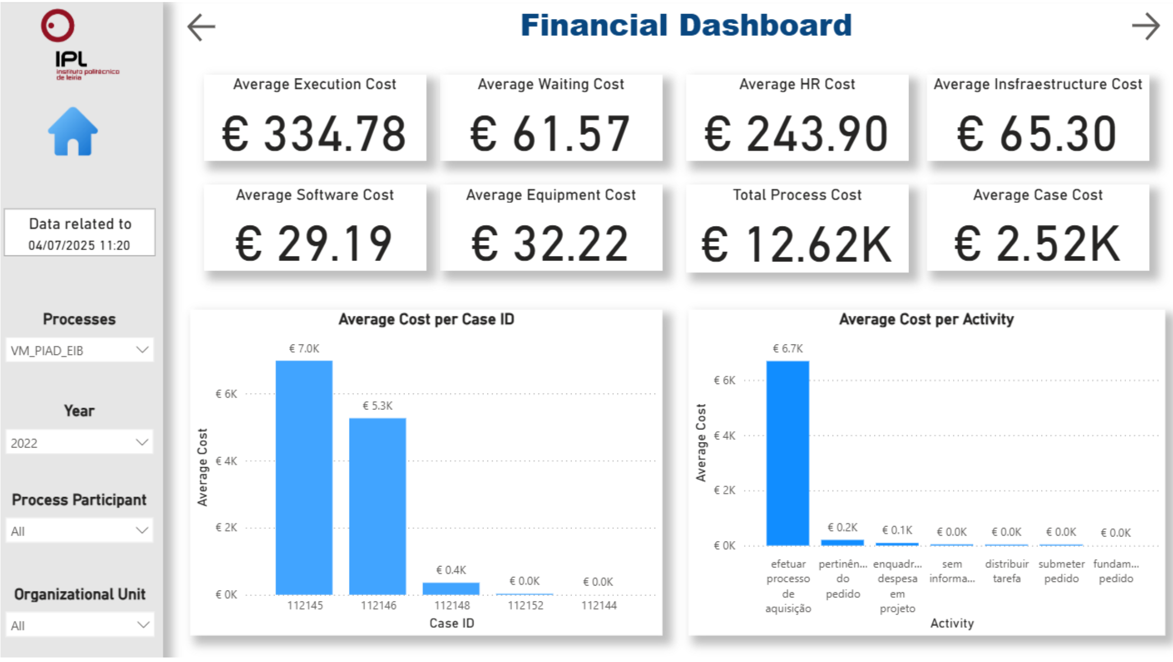

Figure 15- Financial Dashboard (filtered by Year)

Figures 14 and 15 show the Financial Dashboard. Figure 14 presents the estimated cost breakdown for the PIAD_EIB process without filters, while Figure 15 applies the same Year filter used in the KPI Dashboard. This consistency illustrates how cost metrics, such as execution cost, waiting cost and human resource cost, recalculate correctly when the same subset of data is analyzed. By applying equivalent filters, coherence between the KPI and Financial Dashboards was demonstrated, reinforcing their reliability as complementary decision-support tools.

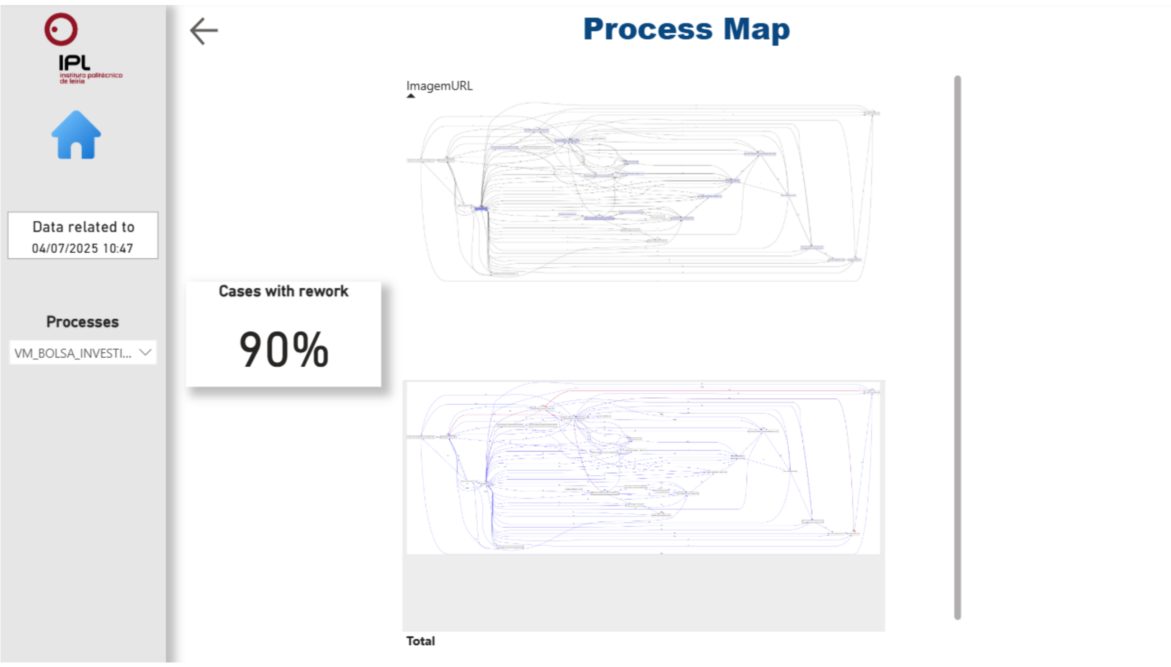

Figure 16- Process Map Dashboard

Due to technical constraints in Power BI, the embedded process maps appear with limited resolution (*512x512 pixels*). However, users can click the image to open a larger, high-definition version in their browser, ensuring usability in practice.

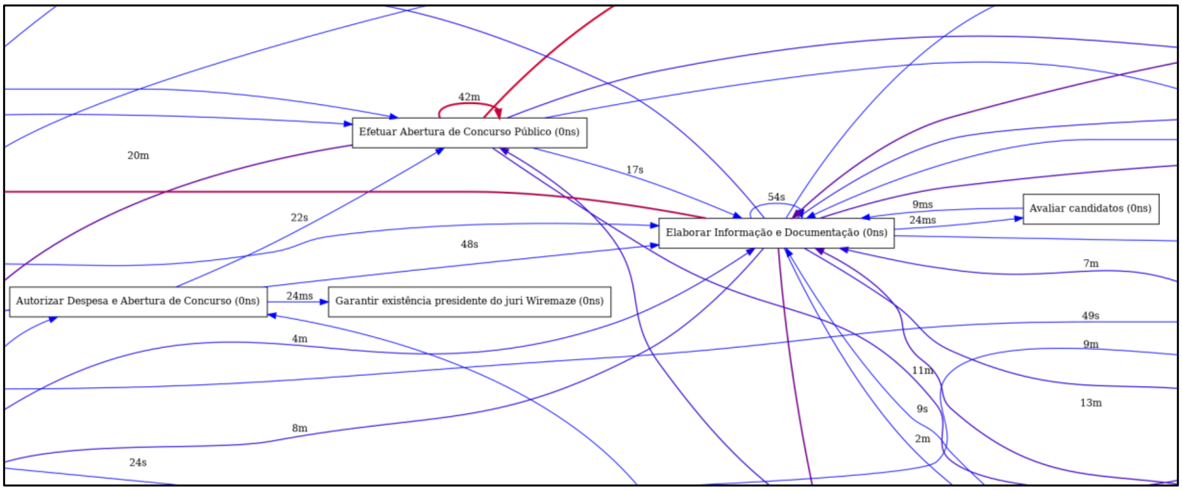

Figure 17- Performance Map

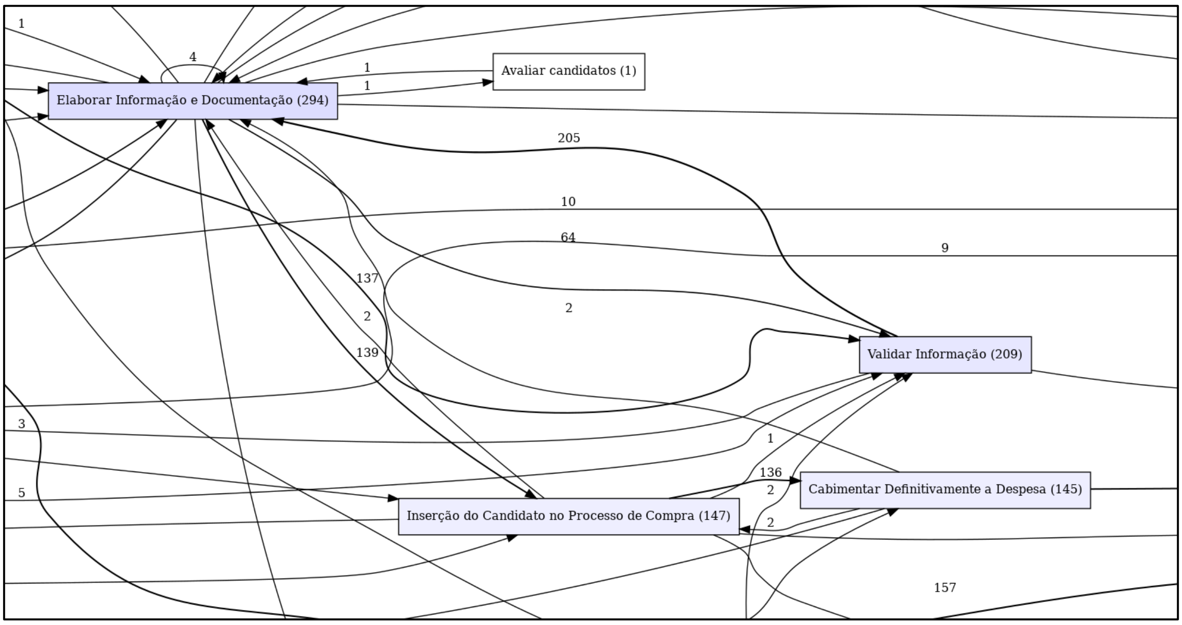

Figure 18- Frequency Map

Figures 17 and 18 display the Process Map Dashboard, which visualizes the execution flow of the scholarship allocation process using Process Mining. Figure 17 presents the performance map, highlighting the average duration between activities, and Figure 18 shows the frequency map, indicating how often specific paths were followed. These visualizations provide valuable insights into where delays occur (e.g., between application submission and document verification) and how frequently alternative paths are used.

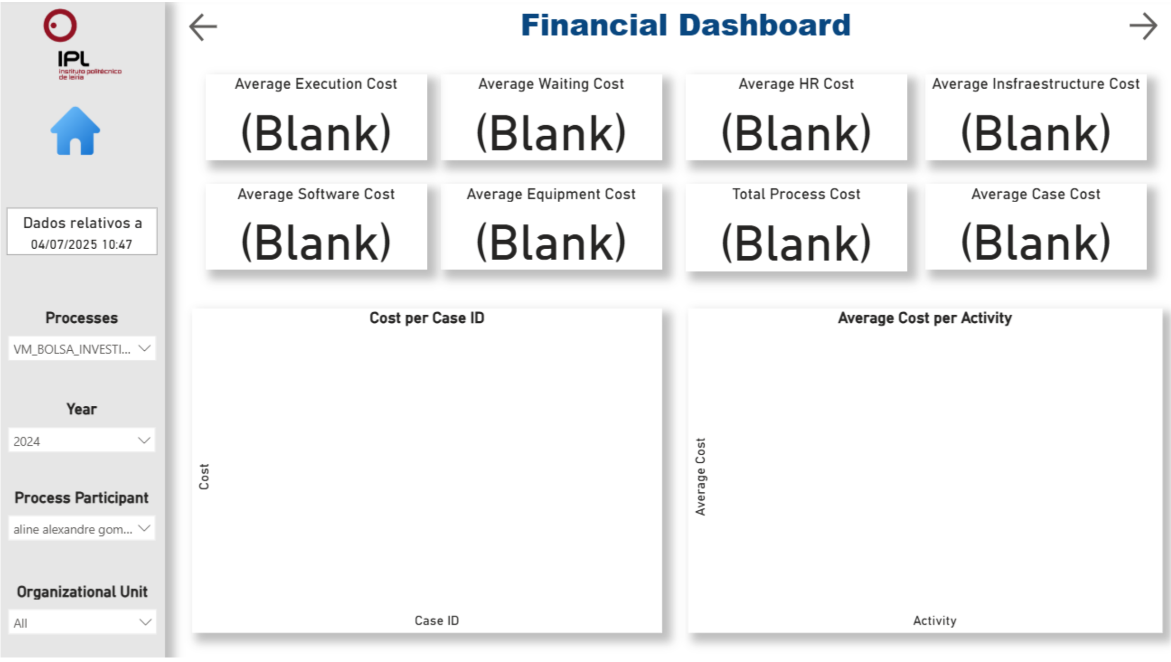

Figure 19- Financial Dashboard in Blanks

Finally, Figure 19 demonstrates how the dashboards handle cases where filters return no data. For testing, the filter was set to the participant *"Alice Alexandre Gomes Pereira."* Since this participant was not associated with any scholarship allocation cases in 2024, the dashboard displayed only blank values. This behavior is desirable, as it prevents misleading information and clearly communicates the absence of relevant records.

In summary, functional testing confirmed that the dashboards for the scholarship allocation process are interactive, coherent, and reliable. Filters work correctly, KPIs update dynamically, costs are recalculated consistently across dashboards, and process maps provide valuable insights into performance and frequency. Even in cases where no data is available, the dashboards handle the situation gracefully, preserving clarity and interpretability.

6.2. Usability Testing

As the final stage of evaluation, the developed dashboards were assessed by a total of 22 institutional stakeholders. To conduct this assessment, the Post-Study System Usability Questionnaire (PSSUQ) was applied, providing a structured means of measuring user perceptions of system usability.

The questionnaire included 23 items in total (Appendix C): three questions related to the professional background of participants and twenty dedicated to the evaluation of the dashboards. Of these, 19 items were closed-ended statements formulated in a positive form, answered on a seven-point Likert scale, where 1 corresponded to "Strongly Agree" and 7 to "Strongly Disagree". An additional open-ended question invited respondents to provide observations and suggestions for improvement.

The scoring of the PSSUQ follows a consolidated methodology in which lower scores indicate higher usability. Results can be reported both as an overall usability score (mean of items 1–19) and as separate dimensions: System Usefulness (SysUse), comprising items 1–8; Information Quality (InfQual), comprising items 9–15; and Interface Quality (IntQual), comprising items 16–18. This multi-dimensional structure enables the identification of strengths and weaknesses in different aspects of system usability.

The analysis of responses revealed an overall average score of 2.75 (SD = 1.03) across items 1–19, with values ranging between 1.0 and 5.16. This indicates a moderately positive evaluation of the dashboards.

When analyzed by dimension, the results were as follows:

- System Use (Items 1–8): mean = 2.53 — indicating that participants generally found the system easy to use, to learn and to operate effectively.
- Information Quality (Items 9–15): mean = 2.98 — this was the least positive dimension, suggesting that the clarity and usefulness of error messages, help texts and on-screen information could be improved.
- Interface Quality (Items 16–18): mean = 2.85 — users reacted positively to the look and feel of the interface, although there is room to make it more engaging and intuitive.

Item-level analysis highlighted specific areas that require attention. The highest scores (poorest evaluations) were observed for the system's error messages (Item 9, mean = 4.00), recovery from errors (Item 10, mean = 3.50), the completeness of functionalities (Item 18, mean = 3.32) and clarity of information (Item 11, mean = 3.23). These results point to the need for more informative error handling, clearer documentation and closer alignment between system functions and user expectations.

On the other hand, several items achieved lower (more favorable) scores, such as ease of use (Item 2, mean = 2.27), comfort in using the system (Item 6, mean = 2.18) and ease of learning (Item 7, mean = 2.18). These responses suggest that users generally adapted quickly and felt comfortable with the dashboards.

Taken together, the findings confirm that the dashboards were perceived as usable and relevant for process monitoring, while also identifying areas for refinement in information clarity, error handling and interface design. The open-ended feedback further reinforced these conclusions, highlighting the need for clearer labelling, more detailed help documentation, and additional guidance for data interpretation. In conclusion, the usability testing validated the technical feasibility and functional value of the dashboards, while providing concrete directions for future iterations to enhance usability, accessibility and user satisfaction.

7. Conclusion and Future Work

7.1. Main Achievements

This project demonstrated that the combination of process mining and business intelligence dashboards can significantly enhance the monitoring of administrative processes in higher education institutions. One of the most relevant contributions of the project was the definition and validation of a comprehensive set of 23 indicators, covering the dimensions of time, cost, compliance and rework. These indicators were carefully designed on the basis of academic literature and adapted to the institutional context. Their validation involved consultation with institutional stakeholders, who confirmed their practical relevance and alignment with the needs of the Polytechnic University of Leiria. This process ensured that the developed KPIs are not only theoretically robust but also applicable in real operational scenarios.

Another significant accomplishment was the development of three interactive dashboards in Microsoft Power BI, each addressing a different but complementary perspective of process performance: time and control-flow, financial cost and process mapping. Together, these dashboards incorporated maximum 4 filters and a wide variety of visual elements, allowing users to explore the data dynamically. By enabling stakeholders to analyze processes from multiple viewpoints, the solution provided a powerful tool to identify inefficiencies, delays and deviations, thereby supporting continuous process improvement.

The project also succeeded in bringing process mining techniques into the institutional environment. Using event logs extracted from the information system, it was possible to discover process variants and visualize activity flows. The process map visualization highlighted activity loops and offered valuable insights into recurring inefficiencies. This integration represented a significant methodological step forward for the institution, as it introduced a data-driven approach to understanding and optimizing processes that had previously been analyzed only through manual inspection.

Finally, the solution was validated through functional testing and direct feedback from stakeholders. The dashboards were tested for accuracy, responsiveness and clarity, and the results confirmed that the visualizations were both usable and useful for decision-making. Stakeholders emphasized the added value of having an integrated and interactive tool to support evidence-based management.

Overall, the project delivered a coherent framework composed of validated performance indicators, three interactive dashboards and a scalable data architecture that can be extended to other processes. By quantifying and structuring the work in this way, the project highlights not only the technical achievements but also the substantial effort invested in ensuring that the solution is both rigorous and impactful.

7.2. Future Work

Future work should focus on expanding and refining the current system to ensure greater scalability and long-term impact.

One important direction is the automation of ETL pipelines, which would reduce the need for manual preprocessing and allow dashboards to be updated in real time.

Another area of improvement involves integrating richer and more detailed financial data, thereby strengthening the accuracy and depth of cost-based KPI analyzes.

In parallel, rework detection could be enhanced by improving the quality and standardization of event logs, enabling the reliable quantification of repeated activities and inefficiencies.

Beyond these technical enhancements, it will also be important for future research to explore comparative studies that evaluate process performance before and after the implementation of improvements. Such studies could systematically track how the removal of bottlenecks, the correction of errors, or the mitigation of recurring failures impacts overall efficiency and costs. Comparative dashboards and graphical visualizations would provide a clear way to highlight performance gains across time, ensuring that the benefits of process optimization are both measurable and transparent.

These comparisons should address both operational indicators and financial indicators. By analyzing both perspectives in parallel, future work will be able to assess not only how processes become faster or more reliable, but also how they become more cost-effective and sustainable.

In addition to these technical and analytical directions, future work should also prioritize improving usability and user experience, as indicated by the questionnaire results presented in Chapter 6.2. Although the dashboards were recognized as useful for process monitoring, stakeholders consistently identified challenges related to ease of use, comfort and learnability. Addressing these aspects could involve refining the interface design, simplifying navigation, and providing clearer legends and documentation to support interpretation. Enhancements in usability would not only increase stakeholder satisfaction but also promote wider adoption and more effective use of the dashboards across the institution.

By combining technical improvements, such as automation, richer data integration and comparative analysis, with human-centered refinements guided by usability feedback, future iterations of the system can evolve into a more robust, accessible and impactful tool.

This dual approach would ensure that the dashboards not only generate high-quality insights but also deliver them in a way that is intuitive and engaging for their users.

Altogether, while the solution developed in this project provides a strong foundation for continuous improvement in process monitoring at higher education institutions, its scalability and long-term relevance will ultimately depend on further automation, improved data quality, deeper institutional integration and rigorous comparative analyzes that demonstrate the concrete impact of implemented changes.

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9. Glossary

Artificial Intelligence (AI): Field of computer science that develops systems capable of performing tasks that typically require human intelligence, such as learning, reasoning and problem-solving;

Business Intelligence (BI): Technologies and methods used to analyze data and support decision-making through dashboards and reports;

Business Process Management (BPM): Discipline involving methods and tools to model, monitor and improve organizational processes;

Extract, Transform, Load (ETL): Data integration process used to move data from multiple sources into a central data warehouse;

Higher Education Institutions (HEIs): Universities, polytechnics and other institutions providing tertiary education;

Key Performance Indicators (KPIs): Quantifiable measures used to evaluate the success of an organization, process, or project;

Organizational Unit (OU): Subdivision within an institution, such as a school or department, responsible for specific activities;

Post-Study System Usability Questionnaire (PSSUQ): Standardized questionnaire to measure user satisfaction after interacting with a system;

Robotic Process Automation (RPA): Technology that uses software robots to automate repetitive tasks in digital systems.

Appendices

Appendix A - PowerPoint from internal training

Tempo médio, máximo, mínimo e mediano de conclusão de um caso

O **tempo médio** é a média do tempo necessário para finalizar os casos, calculada com base no total de casos concluídos. O período pode ser especificado ou não, dependendo da análise desejada.

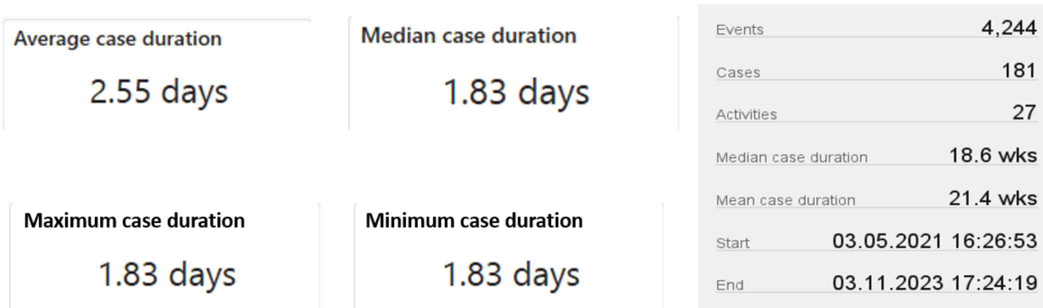
O **tempo máximo** é o período máximo para a resolução do mesmo, contando a partir de sua abertura até sua finalização.

O **tempo mínimo** é o período mínimo para a resolução de um caso, contando a partir de sua abertura até sua finalização.

O **tempo mediano** é o valor que separa a metade mais rápida da metade mais lenta dos tempos de resolução dos casos, indicando um tempo típico de conclusão.

O tempo dos casos pode ser distribuído conforme:
- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, ...).

Tempo médio, máximo, mínimo e mediano de conclusão de um caso



Tempo de Cada Caso

O **tempo de cada caso** é a duração específica entre a abertura e a conclusão de um caso individual.

O tempo de cada caso pode ser filtrado conforme:
- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, ...).

Tempo de Cada Caso

O **tempo de cada caso** é a duração específica entre a abertura e a conclusão de um caso individual.

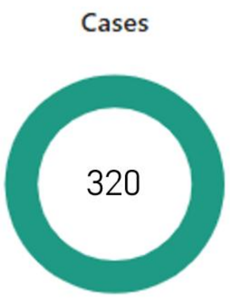
Case ID	Total Duration
83	17d 22h 49m 04s
108	9d 23h 26m 41s
69	9d 19h 00m 19s
92	9d 00h 11m 37s
13	8d 16h 39m 17s
14	8d 16h 38m 07s
44	7d 20h 59m 52s
60	7d 17h 12m 21s
55	6d 23h 54m 15s
61	6d 23h 51m 42s
125	6d 21h 14m 50s
45	6d 17h 17m 46s
1	6d 00h 43m 24s
10	5d 22h 17m 50s
79	5d 22h 16m 30s
29	5d 20h 11m 09s
53	5d 17h 48m 09s
113	5d 15h 24m 18s
77	5d 02h 03m 31s
22	4d 03h 59m 22s

Número total de casos

O **número total de casos** em um sistema corresponde à quantidade total de registros de casos existentes, incluindo os concluídos e os por concluir.

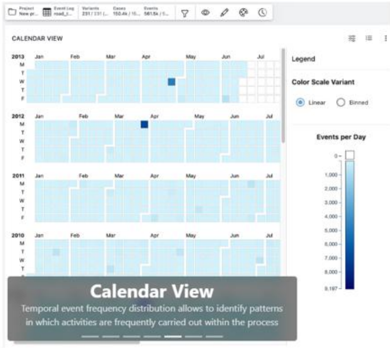
O número total de casos pode ser demonstrado conforme:
- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, ...);
- Estado (aberto, fechado).

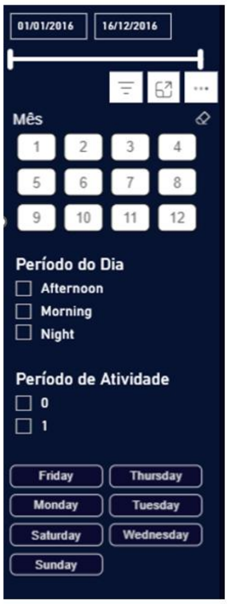
Número total de casos



Área	Count of Cliente
Administrativo	60
Comercial	61
Financeiro	67
Logísitca	58
Operações	75
Total	**320**

Número total de casos





Número total de variantes

O **número total de variantes** é a quantidade de diferentes sequências que um caso pode seguir durante seu processo, dependendo das decisões e eventos em cada etapa. Ele varia conforme a complexidade do processo.

O número total de variantes pode ser demonstrado conforme:

- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, …).

Número total de variantes

O **número total de variantes** é a quantidade de diferentes sequências que um caso pode seguir durante seu processo, dependendo das decisões e eventos em cada etapa. Ele varia conforme a complexidade do processo.

Área	Count of Cliente
Administrativo	60
Comercial	61
Financeiro	67
Logísitca	58
Operações	75
Total	**320**

Duração de cada variante

A **duração de cada variante** é o tempo necessário para completar o processo de um caso seguindo uma sequência específica de etapas e decisões.

A duração de cada variante pode ser filtrada conforme:
- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, ...);
- Atividade.

Duração de cada variante

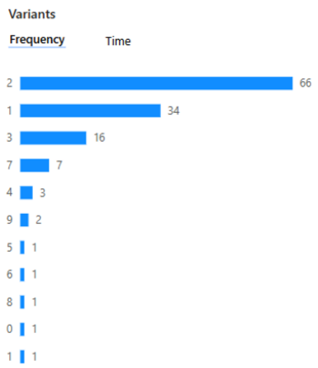
A **duração de cada variante** é o tempo necessário para completar o processo de um caso seguindo uma sequência específica de etapas e decisões.

Frequência de cada variante

A **frequência de cada variante** é o número de vezes que uma determinada sequência de processo ocorre dentro do total de casos analisados.

A frequência de cada variante pode ser filtrada conforme:

- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, ...).



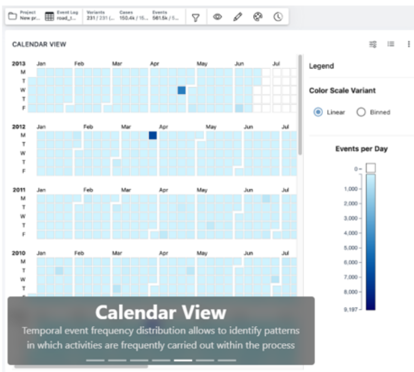
Número total de atividades

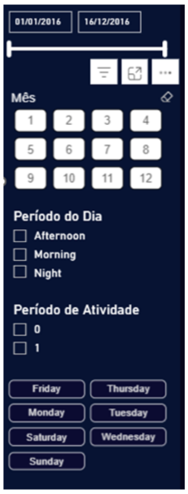
O **número total de atividades** corresponde à todas as atividades distintas executadas.

O número total de atividades pode ser filtrada conforme:
- Unidade Orgânica (UO), Unidade de Investigação (UI), Serviços;
- Interveniente;
- Período (dia, mês, ano, ...).

Nível de atividade realizada por perído de tempo

A **quantidade total de atividades** realizada num período de tempo.

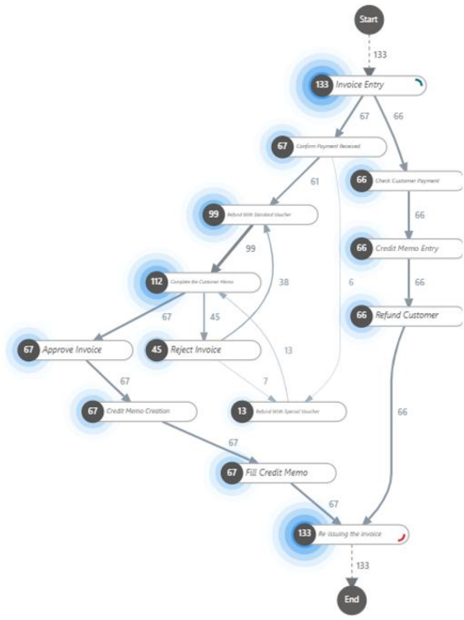




Análise de frequência

A **frequência dos casos** estão representados pela cor azul, quanto mais escuro, maior a frequência.

- Totais
- Case count
- Máxima ocorrência

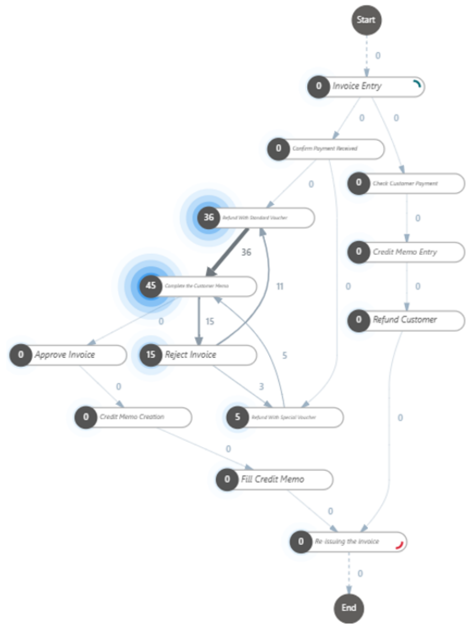


Frequência/Percentagem de retrabalho

A **frequência/percentagem de retrabalho** é a proporção de tarefas que precisaram ser refeitas devido a erros ou falhas.

Rework cases %

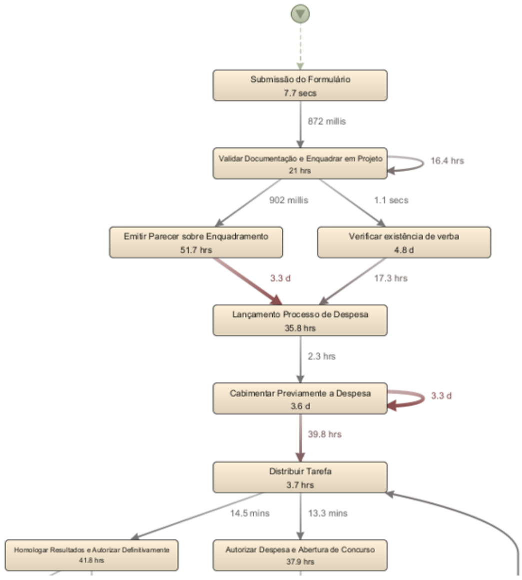
22.56%



Análise de performance

A **análise da performance** dá-nos uma visão geral de como os processos fluem.

- Duração média
- Duração máxima
- Duração mínima



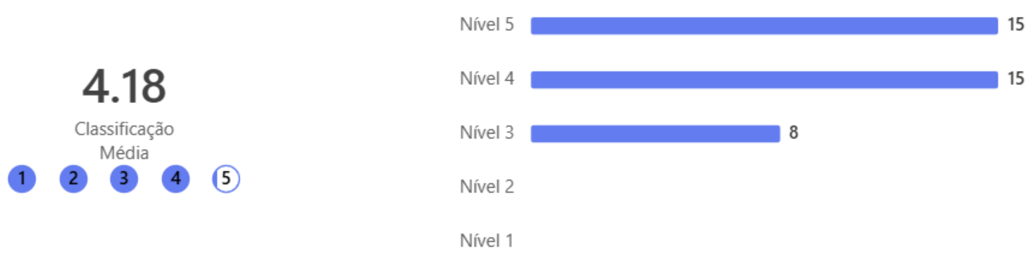
Appendix B - KPI survey results

5. Tempo de conclusão de um caso (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

6. Tempo de cada caso (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

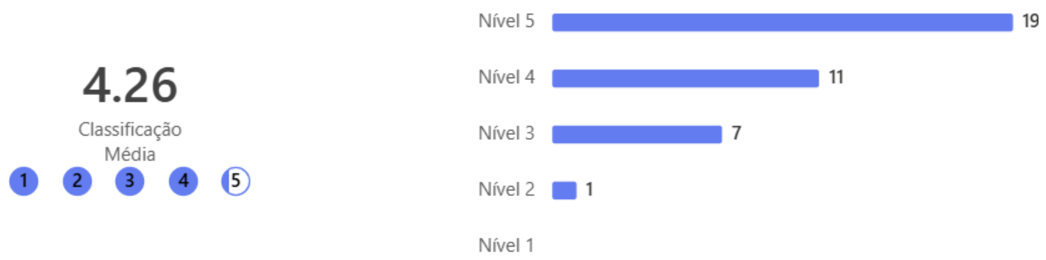
7. Número total de casos (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

8. Número total de variantes (1 - Muito pouco útil; 5 - Muito útil). (0 ponto) Mais

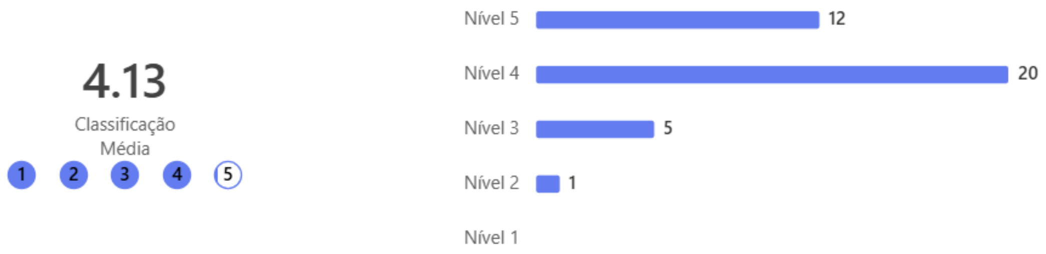


9. Duração de cada variante (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

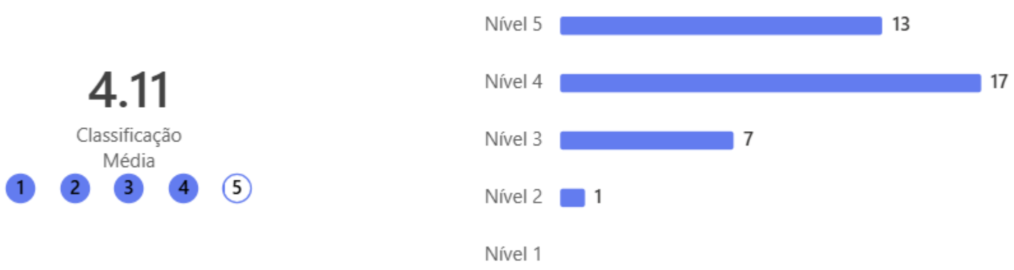
10. Frequência de cada variante (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)



11. Número total de atividades (1 - Muito pouco útil; 5 - Muito útil). (0 ponto) Mai



12. Nível de atividade realizada por período de tempo (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)



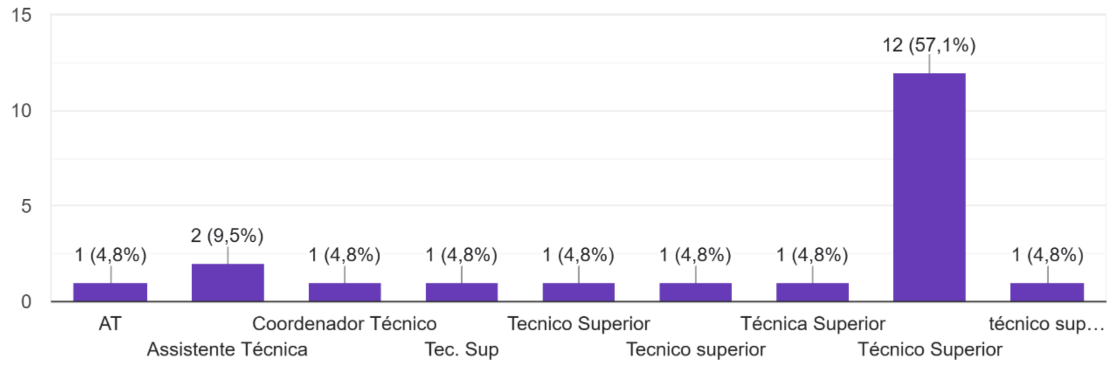
13. Análise de frequência (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

14. Frequência/Percentagem de retrabalho(1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

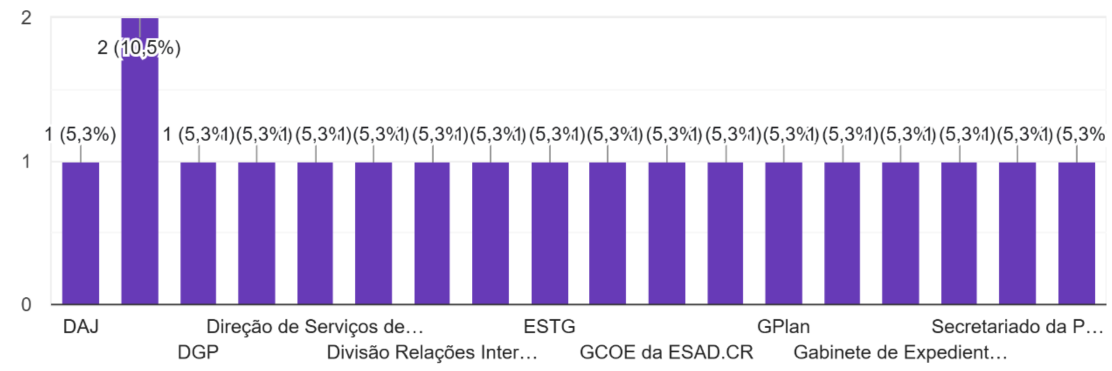
15. Análise de performance (1 - Muito pouco útil; 5 - Muito útil). (0 ponto)

Appendix C - Post-Study System Usability Questionnaire

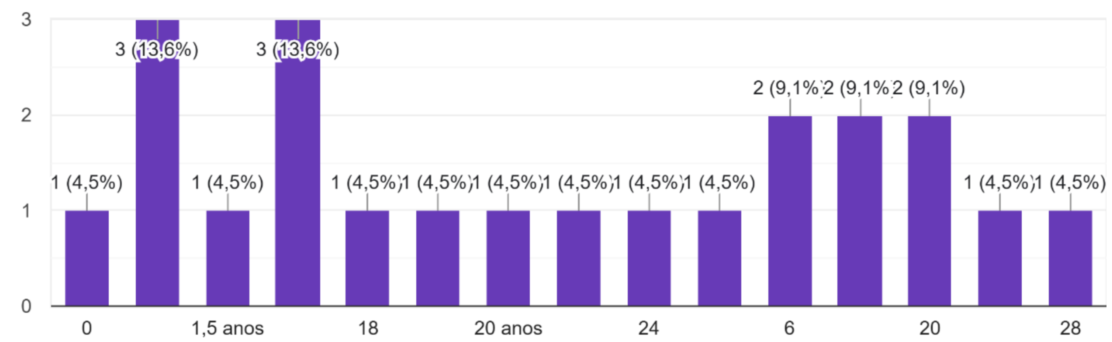
Qual é atualmente a sua categoria?
21 respostas



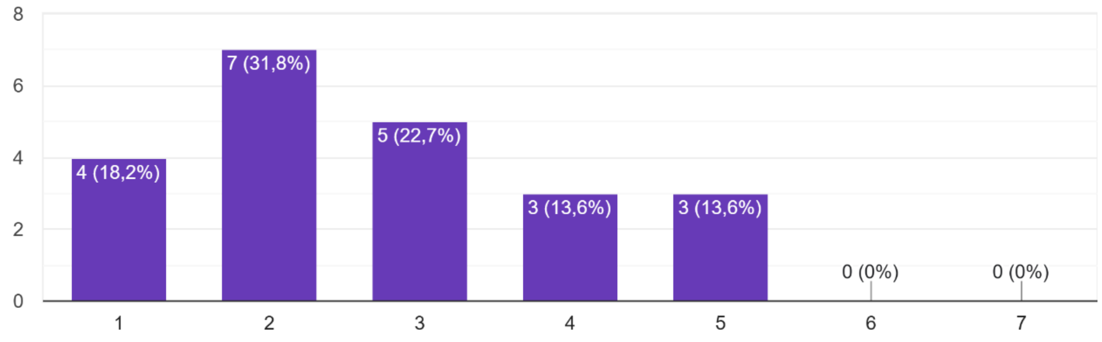
Qual é o serviço/divisão/gabinete a que está afeto?
19 respostas



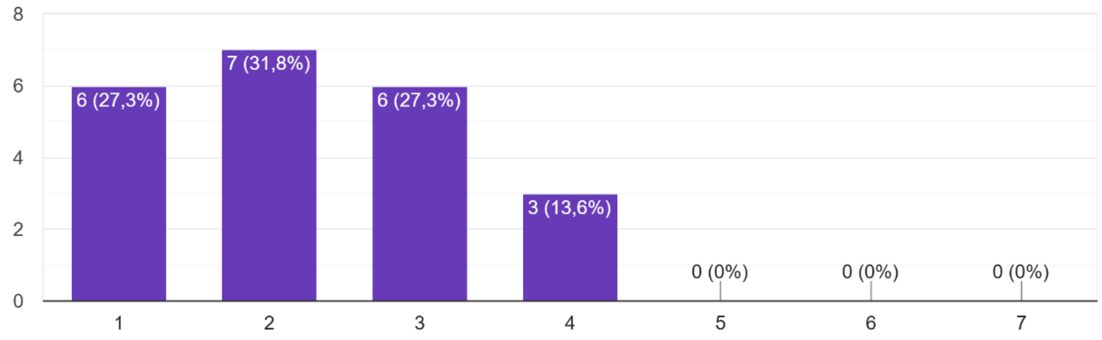
Quantos anos de experiência possui na sua atual função?
22 respostas



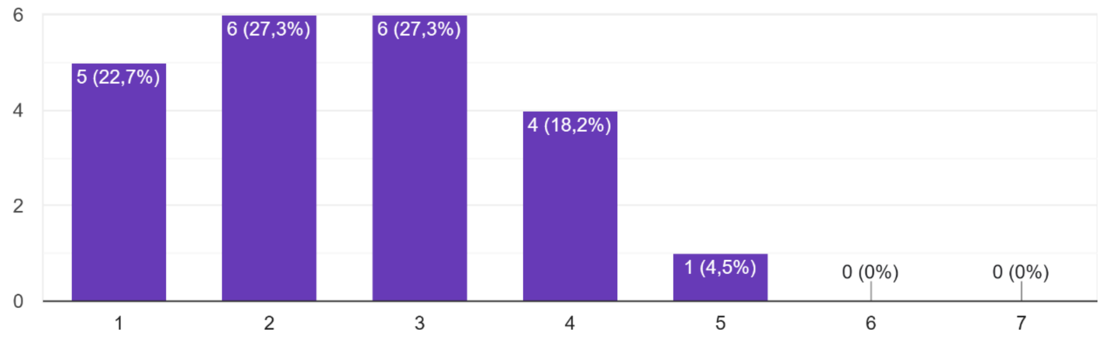
Item 1 - Em geral, estou satisfeito com a facilidade de utilização deste sistema.
22 respostas



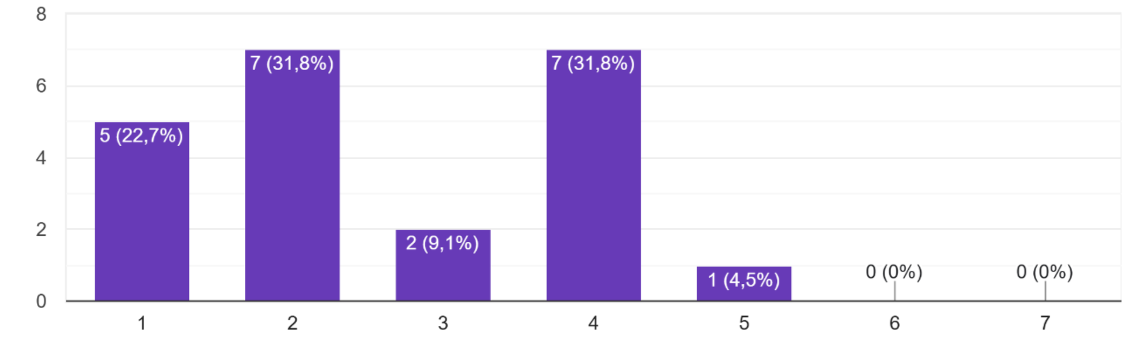
Item 2 - Este sistema foi simples de utilizar.
22 respostas



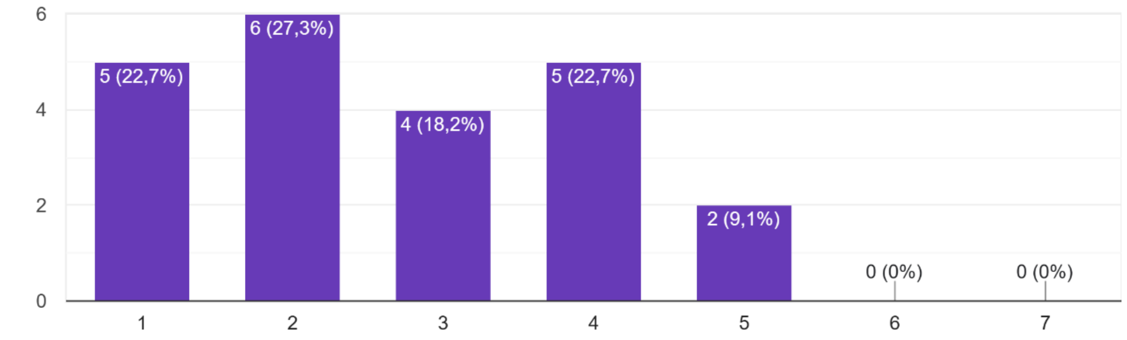
Item 3 - Consegui completar as tarefas e os cenários utilizando este sistema.
22 respostas



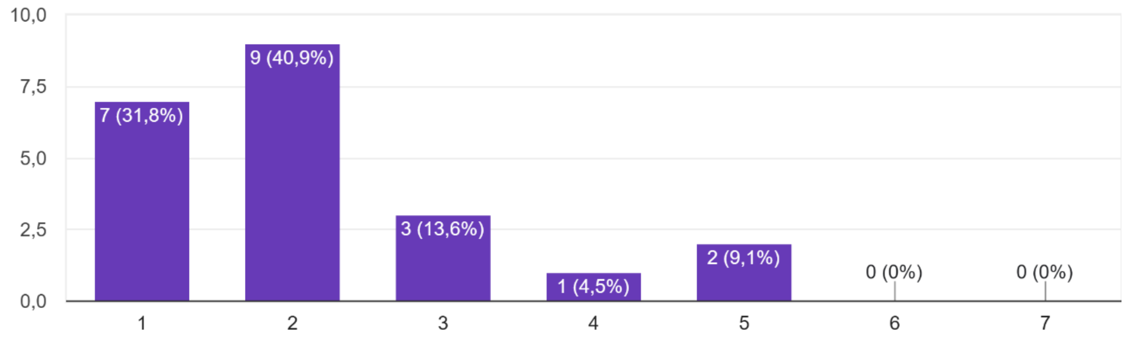
Item 4 - Consegui completar rapidamente as tarefas e cenários utilizando este sistema.
22 respostas



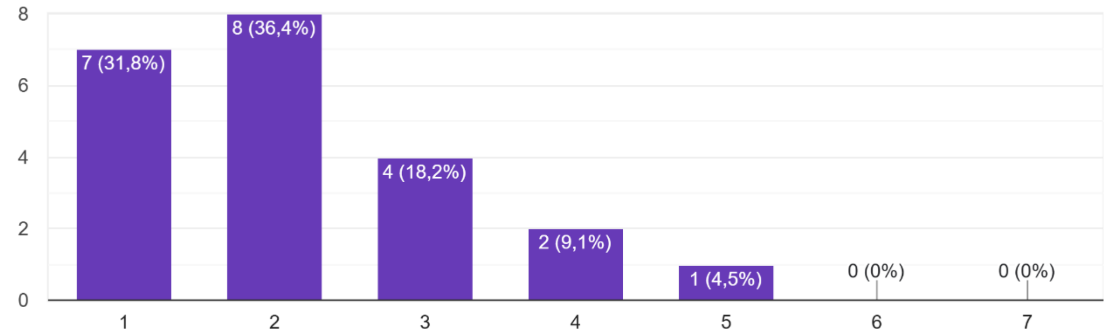
Item 5 - Consegui completar as tarefas e os cenários com eficiência utilizando este sistema.
22 respostas



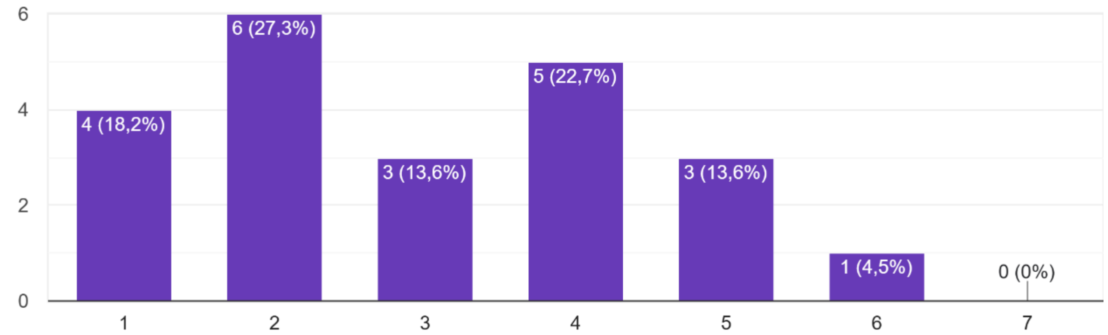
Item 6 - Senti-me confortável a utilizar este sistema.
22 respostas



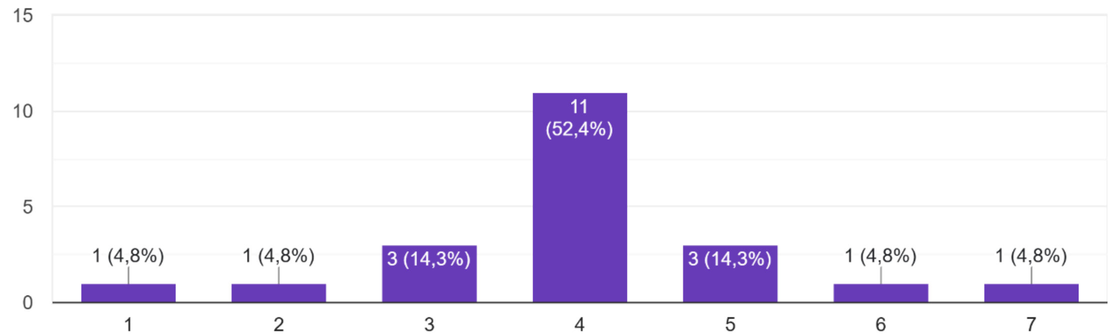
Item 7 - Foi fácil aprender a utilizar este sistema.
22 respostas



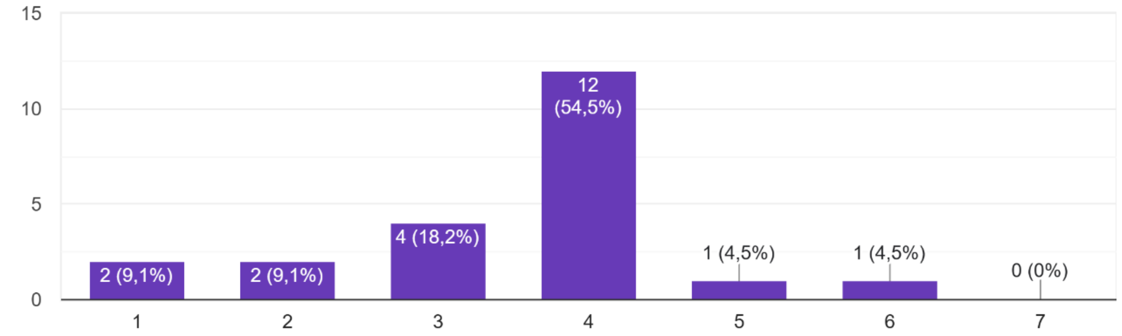
Item 8 - Acredito que me tornaria rapidamente produtivo se utilizasse este sistema.
22 respostas



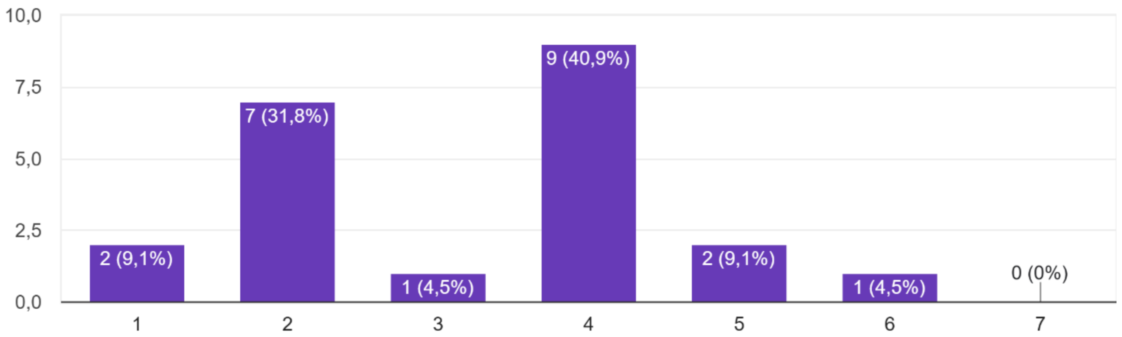
Item 9 - O sistema deu mensagens de erros que me indicaram claramente como resolver os problemas.
21 respostas



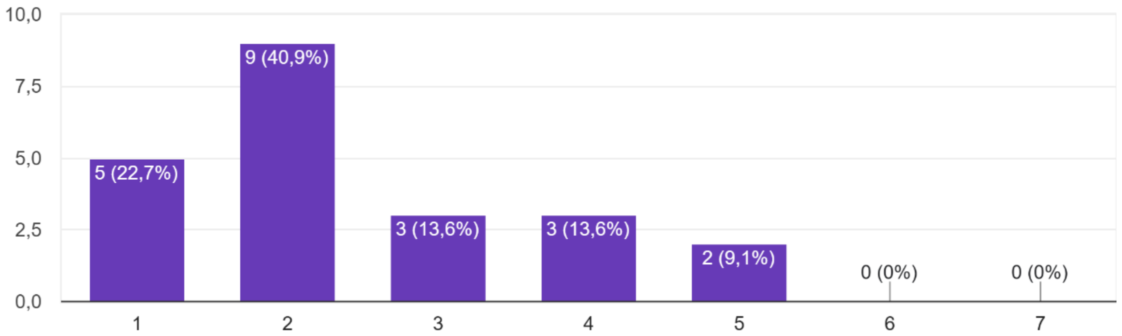
Item 10 - Sempre que cometi um erro durante a utilização do sistema, consegui recuperar de forma fácil e rápida.
22 respostas



Item 11 - A informação fornecida pelo sistema (como ajuda online, mensagens no ecrã ou outra documentação) foi clara.
22 respostas

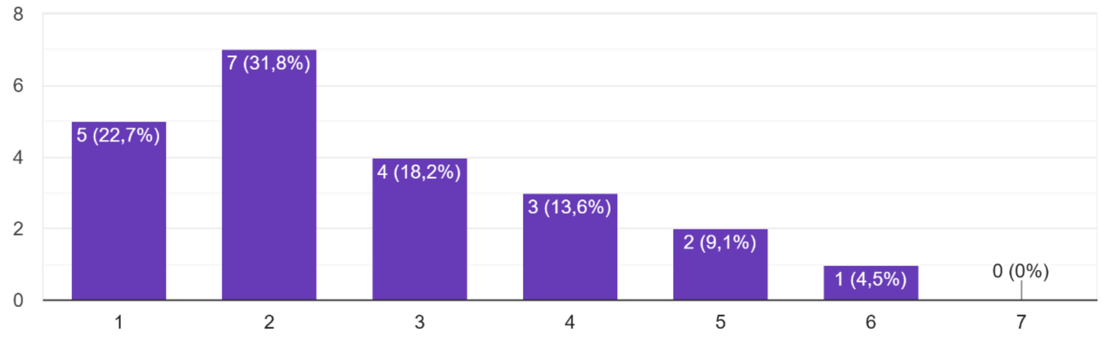


Item 12 - Foi fácil encontrar a informação que precisava.
22 respostas



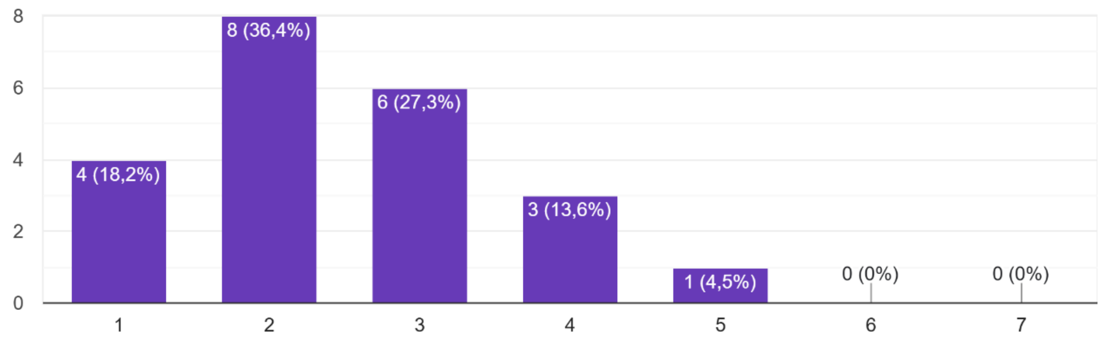
Item 13 - A informação fornecida pelo sistema foi fácil de entender.

22 respostas



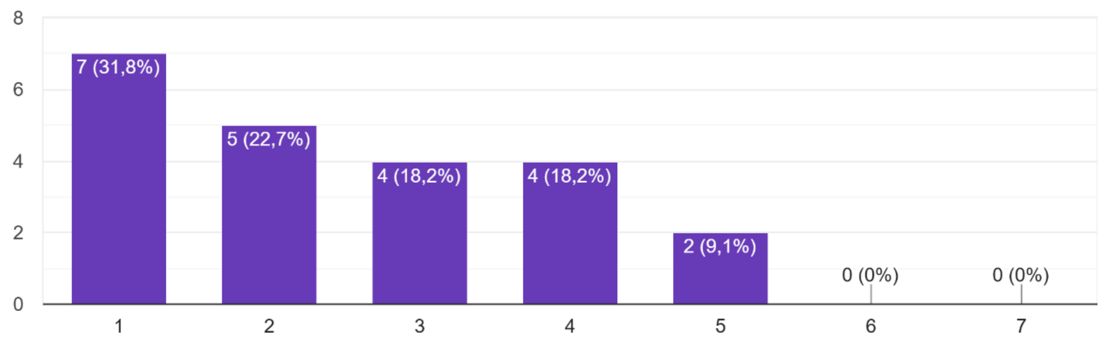
Item 14 - A informação foi eficaz para me ajudar a completar as tarefas e os cenários.

22 respostas

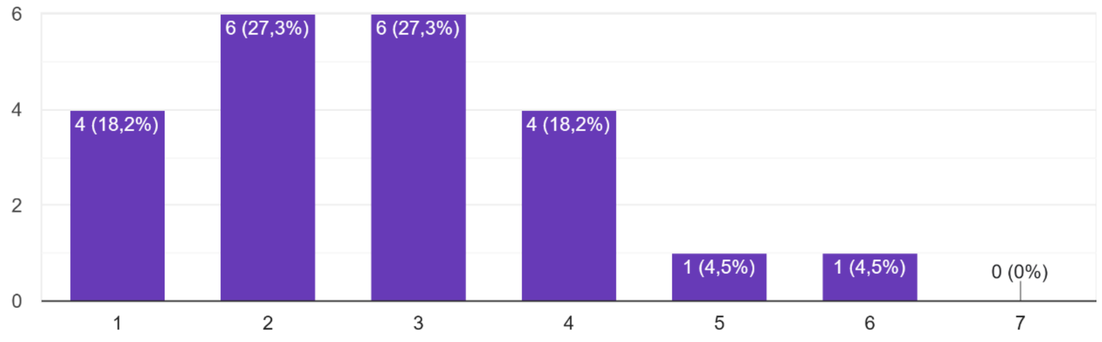


Item 15 - A organização da informação que o sistema transmitiu foi clara.

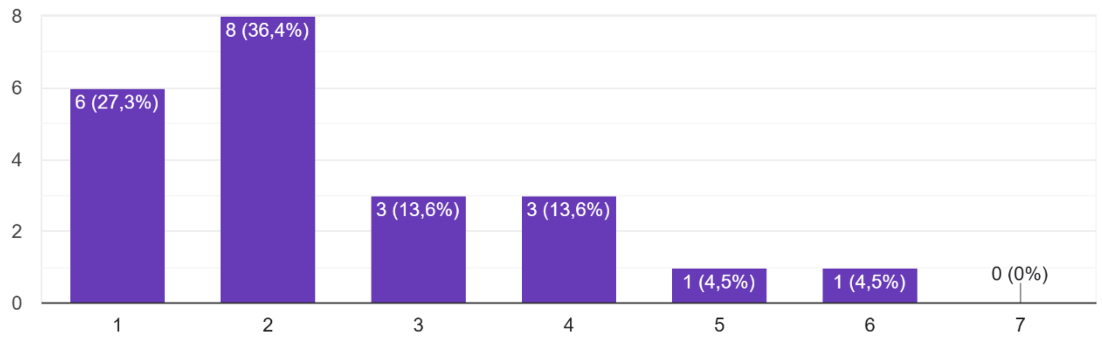
22 respostas



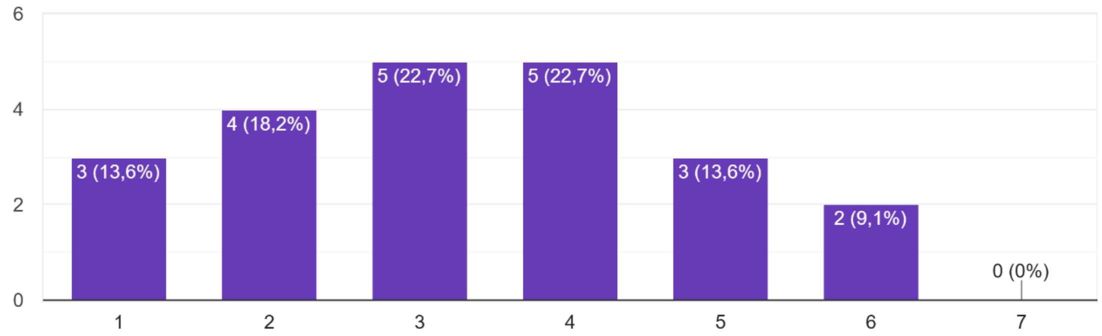
Item 16 - A interface do sistema foi agradável.
22 respostas



Item 17 - Gostei de utilizar a interface deste sistema.
22 respostas



Item 18 - Este sistema tem todas as funcionalidades e capacidades que eu esperava.
22 respostas



Item 19 - Em geral, estou satisfeito com este sistema.
22 respostas