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AI Applications in Planning and Management Control: A Case Study

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Internship report
Master in Modelling, Data Analysis and Decision Support Systems

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Abstract

Artificial Intelligence has had a significant impact on the functioning of organisations. The development of technologies, such as Machine Learning, Large Language Models and Robotic Process Automation, enables real-time analysis of large volumes of structured and unstructured data, identification of complex patterns and automation of repetitive and low-value tasks.

Organisations face challenges due to complex management information models, large volumes of data and time-consuming processes, impacting efficiency and decision-making. To maintain competitiveness in the telecommunications sector in Portugal, organisations seek to integrate Artificial Intelligence technologies, such as Machine Learning and Large Language Models, within their operations, enhancing internal processes and decision support. Additionally, opportunities to explore Artificial Intelligence applications in the area of Robotic Process Automation are being pursued.

This work investigates the potential applications of Artificial Intelligence (AI) within the Planning and Management Control Department. It addresses the increasing complexity and volume of data, which challenge traditional methods and require more efficient and intelligent solutions. While the core objective is to explore how AI, particularly Machine Learning and Large Language Models, can optimise processes and enhance decision-making, the study also recognises that AI is not always the most suitable approach. In some cases, alternative or complementary solutions such as process automation (e.g., Robotic Process Automation) can provide significant value and should be considered as part of a broader strategy for process improvement.

To accomplish this goal, a methodology based on Design Science Research was adopted, focused on identifying organisational problems and proposing and evaluating practical solutions. Data collection were carried out through face-to-face interviews with all employees of the Planning and Management Control Department. With the use of specialised software, this data was processed using thematic analysis, enabling the identification of main themes related to the challenges faced. Based on these findings, both AI and non-AI potential solutions were proposed. Their evaluation were included analysis of feasibility, sustainability and cost-effectiveness, supported by measurable indicators such as Return on Investment (ROI). This methodology ensures the recommended solutions are evidence-based and aligned with the specific needs and constraints of the department.

Keywords: Artificial Intelligence, Planning and Management Control, Machine Learning, Large Language Models, Robotic Process Automation, Design Science Research, and Thematic Analysis.

Resumo

A Inteligência Artificial (IA) tem tido um impacto significativo no funcionamento das organizações. O desenvolvimento de tecnologias, como *Machine Learning*, *Large Language Models* e *Robotic Process Automation*, permite a análise em tempo real de grandes volumes de dados estruturados e não estruturados, a identificação de padrões complexos e a automatização de tarefas repetitivas e de baixo valor.

As organizações enfrentam desafios devido a modelos complexos de gestão da informação, grandes volumes de dados e processos demorados, que afetam a eficiência e a tomada de decisão. Para manter a competitividade no setor das telecomunicações em Portugal, as organizações procuram integrar tecnologias de Inteligência Artificial, como *Machine Learning* e *Large Language Models*, nas suas operações, com o objetivo de aprimorar os processos internos e o suporte à decisão. Além disso, estão a ser exploradas oportunidades para aplicar a Inteligência Artificial na área da *Robotic Process Automation*.

Este trabalho investiga as potenciais aplicações da Inteligência Artificial no Departamento de Planeamento e Controlo de Gestão. Aborda a crescente complexidade e volume de dados, que desafiam os métodos tradicionais e exigem soluções mais eficientes e inteligentes. Embora o objetivo principal seja explorar como a Inteligência Artificial pode otimizar processos e melhorar a tomada de decisão, o estudo reconhece também que a IA nem sempre é a abordagem mais adequada. Em alguns casos, soluções alternativas ou complementares, como a automação de processos (por exemplo, *Robotic Process Automation*), podem proporcionar valor significativo e devem ser consideradas como parte de uma estratégia mais ampla para a melhoria dos processos.

Para alcançar este objetivo, foi adotada uma metodologia baseada na *Design Science Research*, focada na identificação de problemas organizacionais e na proposição e avaliação de soluções práticas. A recolha de dados foi realizada através de entrevistas presenciais com todos os colaboradores do Departamento de Planeamento e Controlo de Gestão. Com o uso de software especializado, estes dados foram processados através de uma análise temática, permitindo a identificação dos principais temas relacionados com os desafios enfrentados. Com base nestes resultados, foram propostas soluções potenciais, tanto com IA como sem IA. A avaliação dessas soluções incluiu análise da viabilidade, sustentabilidade e relação custo-benefício, suportada por indicadores mensuráveis, como o Retorno sobre o Investimento (ROI). Esta metodologia garante que as soluções recomendadas são fundamentadas em evidências e alinhadas com as necessidades e limitações específicas do departamento.

Palavras-chave: Inteligência Artificial, Planeamento e Controlo de Gestão, *Machine Learning*, *Large Language Models*, *Robotic Process Automation*, *Design Science Research*, Análise Temática.

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Glossary

AI: Artificial Intelligence
ANN: Artificial Neural Networks
ATS: Annual Time Savings
BBN: Bayesian Belief Networks
BI: Business Intelligence
CSV: Comma-Separated Values
DAX: Data Analysis Expressions
DL: Deep Learning
DSR: Design Science Research
DSRM: Design Science Research Methodology
ERP: Enterprise Resource Planning
GDPR: General Data Protection Regulation
GenAI: Generative AI
IT: Information Technology
KPI: Key Performance Indicators
LLM: Large Language Models
MCS: Management Control Systems
ML: Machine Learning
MS: Microsoft
MTS: Monthly Time Savings
N/A: Not Applicable
P&L: Profit and Loss statement
ROI: Return on Investment
RPA: Robotic Process Automation
SVM: Support Vector Machines

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Chapter 1

Introduction

1.1 Motivation

Nowadays, an increasing number of companies are introducing new Artificial Intelligence (AI) tools on the market, including advanced systems that enable companies to predict market trends. AI has not only transformed the nature of work, but is also driving an increasing interest in exploring how AI tools, such as predictive analytics and Machine Learning (ML) algorithms, can contribute to sectors that are still under-explored.

In Portugal, the telecommunications sector is one of the most competitive sectors, requiring companies to establish effective strategies that allow them to obtain a competitive advantage and, consequently, preserve their position in the market. In this context, telecommunications companies must be more data driven and be able to analyse and extract more value from large volumes of data, in order to gain competitive advantage. The emergence of AI has enhanced this advantage, as it allows a large volume of data to be analysed quickly and accurately, something that otherwise would be unfeasible. Moreover, AI makes it possible to make more accurate forecasts and identify trends that may be overlooked by humans, helping companies consolidate their competitiveness in the market.

To understand the potential benefits of using AI in the area of Planning and Management Control, NOS, a portuguese telecommunications company, promoted an internship that allows the understanding of the processes and tasks performed in order to evaluate possible ways to integrate AI into its daily activities.

1.2 Problem Definition and Objectives

In Portugal, the telecommunications sector is highly competitive, and as a result, NOS must define strategies that enable an agile response to changes in the market. In that regard, NOS has been focused on identifying and implementing advanced technologies, such as Artificial Intelligence (e.g., Machine Learning) and Robotic Processes Automation (RPA), to maintain its competitive advantage and market position.

The Planning and Management Control Department at NOS faces challenges arising from complex management information models, based not only on large volumes of data coming from different data sources, but also on several time consuming processes. These issues limit the department's efficiency, reducing its ability to provide timely and accurate insights for decision-making.

This internship aims to address these challenges by identifying advanced tools, including Artificial Intelligence, Robotic Process Automation and Business Intelligence platforms like Power BI, that can be integrated into organisational workflows to improve efficiency and support decision-making. Therefore, the objective is to carry out a detailed analysis of the processes and tasks, identify those that could benefit from the implementation of advanced solutions and assess the feasibility of using these technologies in the department.

The success of this internship will be achieved if the solutions identified and proposed allow to optimise the processes of the Planning and Management Control Department. The main objectives include reducing time spent on repetitive tasks, increasing operational efficiency and improving the quality and speed of decision-making. Furthermore, the aim is to simplify workflows, integrating tools and reducing the need to switch between multiple programs to perform the same task.

1.3 Internship Report Structure

The structure of this internship report is organised to reflect the progression of the research process and the development of practical solutions. The work begins in Chapter 1, which presents the motivation, problem definition and research objectives that guide this study.

Chapter 2 explores relevant literature on Planning and Management Control, with a particular emphasis on the integration of advanced technologies such as Artificial Intelligence and Robotic Process Automation in organisational contexts. It also addresses key challenges associated with their adoption.

Following this, Chapter 3 outlines the research methodology, which is based on the Design Science Research framework. This chapter describes the data collection process through semi-structured interviews and details the thematic analysis approach used to interpret the data.

Chapter 4 presents the design and development of the proposed solutions, which directly address the challenges and critical tasks identified through thematic analysis. These include both AI-based and non-AI approaches, aimed at mitigating operational difficulties and improving the efficiency and effectiveness of key processes within the organisation.

In Chapter 5, the internship report moves on to the demonstration phase, where two functional prototypes are illustrated, showcasing their relevance to the identified challenges.

Chapter 6 evaluates the proposed solutions using a set of performance metrics, including time savings, number of removable files, output quality, cost of development and maintenance and Return on Investment (ROI). These results are then analysed to assess their practical impact.

Finally, Chapter 8 concludes the internship report by summarising the main findings, reflecting on the limitations of the study, and offering recommendations for future research and practical implementation.

Chapter 2

Related Work

This chapter explores the integration of Artificial Intelligence technologies within organisational processes. It begins by examining learning agents as adaptive systems capable of enhancing performance through continuous interaction with their environment. Subsequently, the discussion covers various AI applications in data analysis, forecasting and budgeting, highlighting how Machine Learning and Large Language Models improve decision-making and operational efficiency.

The chapter further analyses the role of AI in enhancing Enterprise Resource Planning (ERP) systems and demonstrates how the fusion of AI with RPA transforms traditional automation by enabling the processing of complex and unstructured data. Key examples of tools integrating AI and RPA illustrate practical applications and benefits, including increased efficiency, reduced human error and improved strategic insights.

Finally, the chapter addresses the challenges organisations face in adopting AI technologies, such as skill shortages, data privacy concerns and high costs, underscoring the need for overcoming these barriers to fully realise AI's potential. Hypotheses regarding the impact of AI-enabled RPA on administrative efficiency and financial analysis accuracy are also proposed for further investigation.

2.1 Planning and Management Control

Management Control Systems (MCS) are essential for defining strategies that help achieve organisational objectives effectively (Rikhardsson & Yigitbasioglu, 2018). Despite the lack of a consensus definition, Robert N. Anthony defined management control as "the process by which managers assure that resources are obtained and used effectively and efficiently in the accomplishment of the organisation's objectives" (Anthony, 1965; Strauss & Zecher, 2013).

Management control encompasses a range of activities, including planning, coordination, evaluation and decision-making. Through the connection of these functions, the department enables strategies to be implemented effectively and organisational goals to be achieved (Anthony & Govindarajan, 2007; Rikhardsson & Yigitbasioglu, 2018).

Planning consists of the process of deciding how to implement strategies that allow the expected objectives to be achieved (Anthony & Govindarajan, 2007). Consequently, to make strategic decisions, companies require accurate and efficient forecasting and budgeting procedures (Subrahmanyam, Azoury, & Sarkis, 2024). The budget, which typically covers one year, represents a management plan that details all planned revenues and expenses for that year, with the implicit assumption that positive actions will be implemented to align actual results with the plan. On the other hand, a forecast is an estimate of what is most likely to occur, based on historical data and which predicts market trends using statistical techniques (Subrahmanyam et al., 2024; Sundström, 2024). In this sense, accurate budgets and forecasts allow organisations to make informed decisions that influence their competitiveness (Subrahmanyam et al., 2024).

Additionally, management control focuses on monitoring and evaluating performance in relation to defined plans, with the aim of correcting any deviations. The main activities include defining performance indicators, analysing variations and implementing corrective measures. In short, it is essential to analyse the current performance in relation to the budget for each cost center, identifying the causes of variations and recommend actions to correct such deviations, ensuring alignment with the original budget (Anthony & Govindarajan, 2007; Oliveira & Ribeiro, 2023; Subrahmanyam et al., 2024).

With the incorporation of advanced tools and technologies, the market has become more competitive, requiring organisations to make decisions more quickly and accurately. Traditional analysis methods based exclusively on historical data have been replaced by more dynamic approaches that incorporate real-time and predictive analyses, providing greater precision in decision-making. In this context, Artificial Intelligence and Robotic Process Automation emerge as key technologies that complement and enhance the capabilities of planning and management control processes (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017).

2.2 Artificial Intelligence

The development of new technologies, such as Artificial Intelligence, has transformed many aspects of life, including the way organisations make decisions. Within organisations, the introduction of Artificial Intelligence has revolutionised some areas, driven by recent breakthroughs in Machine Learning, Deep Learning (DL) and Large Language Models (LLM) (Sundström, 2024).

Traditionally, decision-making in organisations relied on deductive approaches, where predefined rules and models were dominant. Nowadays, with the development of AI tools, organisations have moved to an inductive approach, where data guides predictions and strategies (Sundström, 2024). This evolution has reshaped the interaction between data and predictive thinking, allowing organisations to take advantage of existing AI tools to deal with complexities previously considered unsolvable.

Artificial Intelligence refers to the ability of a system to process data, identify patterns and make predictions through iterative learning (Chui & McCarthy, 2020; Haenlein & Kaplan, 2019). There are several types of AI systems, including Generative AI (GenAI), which focuses on creating content, and others systems like Machine Learning, which focus on data analysis and forecasting. Nowadays, with the widespread connectivity of individuals, large volumes of data are generated, making it impossible for companies to analyse all available information manually (Haenlein & Kaplan, 2019). AI has revolutionised the way organisations work, since with AI tools, companies can process large volumes of data in real time, identify trends and make decisions that were previously impossible to achieve with the capacity human (Božič & Dimovski, 2019; Schildt, 2017).

Additionally, by using these tools, organisations can reduce the risk of bias in decision-making, as tasks performed by humans are susceptible to being influenced (Haenlein & Kaplan, 2019). Looking forward, AI systems will be used regularly in the future, as these systems can help mitigate biases in decision-making processes (Haenlein & Kaplan, 2019; Hasan, Vaz, Athota, Désiré, & Pereira, 2023).

2.3 AI Applications

The integration of advanced tools enables the analysis of a large volume of data, identification of patterns and forecasting. By using these tools, companies are able to make faster, more informed and efficient decisions, enhancing their ability to achieve strategic objectives (Gupta et al., 2024; Monod, Mayer, Straub, Joyce, & Qi, 2024; Oliveira & Ribeiro, 2023; Rikhardsson & Yigitbasioglu, 2018).

The use of Machine Learning in budgeting and forecasting is transforming organisations by providing valuable insights that improve their decision-making capabilities, making them faster and more accurate. Machine Learning is a field of Artificial Intelligence focused on developing algorithms that can learn patterns from data and make predictions or decisions without being explicitly programmed for each specific task. Several Machine Learning techniques can be categorised into supervised, unsupervised and reinforcement learning, each with their own applications (Chui & McCarthy, 2020; Li, Sigov, Ratkin, Ivanov, & Li, 2023; Subrahmanyam et al., 2024). These approaches vary depending on the type of data used and the way the models are trained. Supervised learning is ideal for predicting tasks because it uses labeled data, which means that for each input there is an associated output. Among the most common models are decision trees and linear regression. On the other hand, unsupervised learning is used to identify patterns as it works with unlabeled data with no predefined outcomes associated with the inputs. Models like K-means clustering are used for cluster analysis and anomaly detection. Finally, reinforcement learning is used in dynamic environments where systems optimise their actions through trial and error, such as in the strategic allocation of resources. Models like Q-learning are often used for resource allocation tasks (Chui & McCarthy, 2020; Li et al., 2023; Oliveira & Ribeiro, 2023; Sundström, 2024; Yang, Liu, Fan, & Yang, 2023).

The development of Large Language Models has brought significant advances in data analysis tasks in organisations. Large Language Models are advanced Machine Learning models trained on massive amounts of textual data, designed to understand, generate and interact using human language. By integrating these models into analysis tools, it is possible to consult and interact with data naturally, without the need to insert formulas, as occurs in ChatGPT. Furthermore, the implementation of these tools allows the creation of insights, reports and dashboards in a simple way, based on descriptions in natural language, facilitating data access and interpretation. These LLM models are increasingly used, as they allow for improved analysis efficiency and, consequently, decision-making (Sundström, 2024).

2.3.1 Data Analysis

Data analysis is one of the most important functions of Planning and Management Control, as it allows the analysis of large amounts of data, the production of insights, the identification of patterns and the making of forecasts. One of the major challenges faced by organisations is the manual collection and analysis of data due to the complexity and high volume of datasets, as it is necessary to collect data from multiple external and internal sources and group them into a single database. However, data analysis is essential as it provides valuable insights that influence its decision-making, which allows the organisation to maintain its competitive advantage and, consequently, its position in the market. (Božič & Dimovski, 2019; Gupta et al., 2024; Perdana, Lee, Koh, & Arisandi, 2022; Rikhardsson & Yigitbasioglu, 2018; Subrahmanyam et al., 2024).

The incorporation of Artificial Intelligence has transformed the way organisations operate in several aspects. With the use of these tools in data analysis, organisations are able to process, interpret and visualise large amounts of data more quickly and efficiently. Additionally, these tools enable real-time data collection, from both external and internal sources, more quickly and effectively, reducing the likelihood of errors occurring related to the integration of different sources (Oliveira & Ribeiro, 2023). Another advantage is the ability to identify insights that would be unattainable through human effort alone, supporting more informed and strategic decision-making processes (Božič & Dimovski, 2019; Schildt, 2017; Subrahmanyam et al., 2024). Futhermore, interactive and dynamic AI-powered reports and dashboards provide clear and detailed visualisation of data, making analysis more intuitive and accessible (Appelbaum et al., 2017; Oliveira & Ribeiro, 2023).

As an example, Tableau Agent is a tool that integrates LLM capabilities, which allows users to query data sets in plain language, similar to ChatGPT. Through a chatbot, users can ask questions and make requests naturally, analysing large volumes of data. Tableau Agent responds fluidly, automatically creating reports, interactive and dynamic dashboards, and even complex calculations. In addition to creating visualisations, the tool offers accurate insights to the organisation, making the data analysis process more efficient and effective. This way, companies can make faster and more informed decisions, boosting productivity and competitiveness (Appelbaum et al., 2017; Tableau, 2024a).

2.3.2 Forecasting

Forecasting is one of the crucial processes for companies, as it influences strategic decision-making. This process allows to predict market trends, based on historical data and simplified models (Anthony & Govindarajan, 2007). Traditionally, models such as exponential averages, time series analysis, basic moving averages and linear regression are widely used. However, these methods have limitations, especially in high volatility scenarios or when dealing with non-linear data. They often struggle to incorporate external factors such as sudden economic shifts or consumer behavior changes, which reduces their effectiveness in dynamic environments. Furthermore, these models are very time-consuming due to the need for constant manual adjustments to reflect new market conditions, which made the process inefficient and error-prone (Li et al., 2023; Subrahmanyam et al., 2024).

The introduction of AI tools, such as Machine Learning and Deep Learning, has revolutionised forecasting processes in organisations (Sharma et al., 2024). With these tools, organisations are able to analyse a large volume of data in real time and detect non-linear patterns, enabling more accurate predictions that would be impossible with traditional methods. Moreover, these tools enable organisations to analyse data in real time and, consequently, adjust their forecasts automatically, allowing rapid and effective adaptation to market changes (Appelbaum et al., 2017; Gupta et al., 2024; Subrahmanyam et al., 2024; Sundström, 2024).

With regard to ML models, as discussed in Chapter 2.3, supervised algorithms, such as Artificial Neural Networks (ANN), boosting models, Bayesian Belief Networks (BBN) and Support Vector Machines (SVM), are often used to make predictions based on historical data. These algorithms are effective, since they require labeled data, that is, datasets that already have known results, to train the model and allow it to identify patterns and make predictions based on these previously established patterns. By using these models, organisations can prepare more accurate forecasts (Appelbaum et al., 2017; Gupta et al., 2024; Subrahmanyam et al., 2024).

As an example, Tableau Einstein Discovery is a tool that integrates AI to make predictions automatically and intuitively. Based on the data content, the tool uses methods that it considers most appropriate to generate predictions. Additionally, it provides insights into the factors that most influence these predictions, allowing for a deeper understanding. The tool also suggests improvements to optimise certain predictions, making the decision-making process more efficient and informed. Another key feature is its user-friendly interface, which allows professionals without extensive technical knowledge to leverage advanced AI capabilities, democratising access to predictive analytics across organisations (Appelbaum et al., 2017; Tableau, 2025).

2.3.3 Budgeting

The budget is a management plan that covers the period of one year and details all income and expenses for that year. It is based on the principle that all necessary actions will be implemented to align actual results with those planned (Anthony & Govindarajan, 2007). The purpose of developing this plan is to avoid financial waste, prioritise investments and maintain the financial stability of an organisation. By setting limits, companies can, over time, compare current performance with planned performance, identify variations and make the necessary corrections to ensure that established goals are met. Traditionally, the budget plan used to be static, which limited the flexibility of organisations to adapt it according to market changes (Subrahmanyam et al., 2024).

With the advancement of AI tools, the budgeting process has become more dynamic, allowing for continuous, rapid and efficient allocation of resources in real time, which maximises productivity and enables adaptation to constantly changing conditions. Furthermore, these advanced technologies allow real-time monitoring of actual costs, facilitating the analysis of variations and the identification of their causes, which enables the agile implementation of corrective actions (Gupta et al., 2024; Sharma et al., 2024; Subrahmanyam et al., 2024).

As an example, Tableau Pulse is an innovative tool that integrates AI and real-time data analytics to help organisations make more informed decisions. This platform allows companies to track the performance of their key indicators, providing valuable and actionable insights instantly. Using AI, Tableau Pulse automatically adapts to changes in data, providing personalised notifications and recommendations that help teams stay ahead of critical events and trends. This allows companies to act more quickly, optimise processes and maximise operational efficiency, significantly improving the decision-making process (Tableau, 2024b).

2.3.4 ERP Systems

Enterprise Resource Planning (ERP) systems are integrated systems designed to manage and coordinate all of an organisation's resources and information. These systems allow the integration of different data sources into a central database, enabling real-time access to all recurring information from the company's different departments, improving decision-making and management control. With automatic data entry, data integration and collection are less susceptible to human error, resulting in higher data quality. This improvement in data quality enhances data analysis, enabling the creation of better insights that have a major impact on decision-making (Appelbaum et al., 2017; Oliveira & Ribeiro, 2023).

With the integration of AI, ERP systems have significantly expanded their analysis and forecasting capabilities. Since this introduction, these systems have become capable of processing both structured and unstructured data, gaining advanced functionalities, such as Machine Learning. This enabled systems to perform real-time analysis, identify trends, predict future scenarios and generate valuable insights for strategic decision-making (Appelbaum et al., 2017; Sharma et al., 2024).

Combining ERP systems with AI technologies offers organisations a significant competitive advantage. By automating tasks and using advanced analysis and forecasting tools, these systems generate valuable insights for decision-making. This enables companies to adapt quickly to an increasingly complex and dynamic market, helping them maintain and strengthen their competitive position (Oliveira & Ribeiro, 2023).

2.3.5 Automation Process

Furthermore, AI tools have leveraged Robotic Process Automation, enabling the automation of low-value and repetitive tasks (Oliveira & Ribeiro, 2023). Before the implementation of RPA, many organisations relied heavily on manual processes to carry out low-value, repetitive and time-consuming tasks, such as data collection and processing. These tasks consumed significant amount of employees' time and diverted their attention away from more strategic and high values activities (Oliveira & Ribeiro, 2023; Sundström, 2024).

The implementation of Robotic Process Automation has resulted in a significant increase in the efficiency of organisations by simplifying low-value, repetitive and time-consuming tasks, such as data collection and processing, significantly reducing the risk of human error. As a result, implementing RPA has enabled users to direct their time towards more strategic and creative tasks, freeing them from repetitive and time-consuming tasks (Oliveira & Ribeiro, 2023; Sundström, 2024).

It is important to note that while AI and RPA are often discussed together, they are fundamentally different technologies. RPA typically involves automating structured, rule-based tasks without requiring learning or decision-making capabilities, whereas AI involves systems that can learn from data and make predictions. Although RPA can function independently, the integration of AI with RPA enhances the ability to automate more complex and unstructured processes.

However, without the AI, these automation processes are limited to programmed rules designed to perform repetitive and structured tasks, such as transferring data between non-integrated systems or creating structured database reports. The integration of AI into RPA has further improved the operational efficiency of organisations, as it allows the automation of tasks to be combined with the processing of more complex processes. By combining Machine Learning with RPA systems, these systems have the ability to interpret structured and unstructured data, with the purpose of identifying trends, making predictions and providing valuable insights for business decision-making (Li et al., 2023; Monod et al., 2024; Oliveira & Ribeiro, 2023, 2021; Sundström, 2024; Yang et al., 2023).

As an example, UiPath is one of the RPA tools that allows to automate processes, and by integrating UiPath with Tableau, organisations can automate data collection and preparation, automatically sending it to Tableau. With Tableau's Artificial Intelligence functionalities, organisations can perform analysis, identify trends and make predictions. Furthermore, by combining Tableau with this tool, it is possible, through chatbots and natural language, to interact with data, requesting analyses, creating dynamic and creative reports and dashboards. In addition to providing valuable insights for decision-making (Tableau, 2024c).

2.4 Challenges in Adopting AI in Organisations

The introduction of Artificial Intelligence into organisations has revolutionised the way they operate, enabling the analysis of large volumes of data, the identification of trends and the making of predictions that would be impossible to achieve with human capacity alone. However, AI integration also brings significant challenges for organisations (Oliveira & Ribeiro, 2023; Subrahmanyam et al., 2024).

One of the main challenges faced by organisations is the lack of IT knowledge among professionals in the accounting and finance areas. The introduction and use of AI tools requires a high level of expertise in statistical analysis and Machine Learning. However, many of these professionals lack these skills, which forces companies to hire IT or data science specialists for tasks that would traditionally be performed by accountants and financial analysts. To face these challenges, it is essential that professionals in these areas seek to improve their IT and data science skills, in order to be better prepared to deal with new market demands (Oliveira & Ribeiro, 2023; Sundström, 2024).

Furthermore, the opacity of AI tools poses a serious obstacle to user trust and adoption. The complexity of Machine Learning methods often makes it difficult to understand how decisions are performed, which can lead to skepticism and reluctance to trust the insights produced by these tools. This distrust can lead users to ignore the insights provided, choosing not to use them as a basis for important decisions that impact the organisation (Monod et al., 2024).

Data privacy and security are a source of concern in the adoption of AI tools. Organisations must ensure that sensitive data used is protected from unauthorised access and breaches. Additionally, they need to comply with laws governing data protection, such as the General Data Protection Regulation (GDPR) in Europe (Subrahmanyam et al., 2024).

Finally, the high costs associated with AI tools represent one of the main obstacles to their adoption in organisations. In addition to the initial investment in hardware and software, companies face ongoing expenses for system upgrades, maintenance and employee training. These financial challenges may restrict the use of these technologies, especially for organisations with limited resources (Appelbaum et al., 2017; Perdana et al., 2022).

In summary, AI offers an enormous potential to transform organisations, promoting efficiency, automation and better decision-making. However, its adoption faces significant challenges, such as high costs, lack of technical skills and the need to overcome barriers related to trust and understanding of the technologies. Overcoming these obstacles will be crucial for organisations to fully realise the benefits of AI (Appelbaum et al., 2017; Monod et al., 2024; Oliveira & Ribeiro, 2023; Perdana et al., 2022).

The challenges identified in the literature regarding the adoption of Artificial Intelligence, namely the lack of technical skills among management professionals, concerns about data privacy and security, as well as high implementation costs, are also evident in the context of the Planning and Management Control Department. This department is confronted with complex information models derived from multiple data sources and time-consuming processes that hinder operational efficiency and timely decision-making. In light of these constraints, it is essential to adopt a methodological approach that enables a systematic understanding of these challenges while also supporting the design of innovative and context-appropriate solutions. Therefore, this internship report employs the Design Science Research methodology, which provides a rigorous framework for analysing organisational needs, designing and developing technological artefacts and evaluating their effectiveness. By adopting this approach, the study ensures that the theoretical insights from the literature are meaningfully aligned with the practical realities of the department, thereby fostering the development of relevant, feasible and sustainable solutions.

Chapter 3

Methodology

The Design Science Research (DSR) methodology was selected for this study due to its focus on solving practical problems through the creation and evaluation of innovative artifacts. This methodology aims to develop technological solutions that satisfy the organisation's needs. These solutions, called artifacts, which can include models, methods, tools or systems, are developed to improve the effectiveness and efficiency of organisations (Hevner, March, Park, & Ram, 2004; Meyer & Henke, 2023).

The Design Science Research Methodology (DSRM) model, proposed by Peffers et al. (2007), as presented in Figure 3.1, structures the research process into six interrelated phases: problem identification and motivation (Phase I), definition of the objectives for a solution (Phase II), design and development (Phase III), demonstration (Phase IV), evaluation (Phase V) and communication (Phase VI). Although these phases are presented sequentially, an essential characteristic of DSRM is its inherently iterative nature. The methodology does not impose a strictly linear progression, as it encourages iterative cycles between phases, enabling researchers to revisit earlier stages, like refining the problem definition or redesigning the artifact, in response to insights gained during later phases such as demonstration or evaluation. This iterative flexibility enhances the methodological robustness and adaptability to complex and evolving problem contexts (Meyer & Henke, 2023; Peffers et al., 2007).

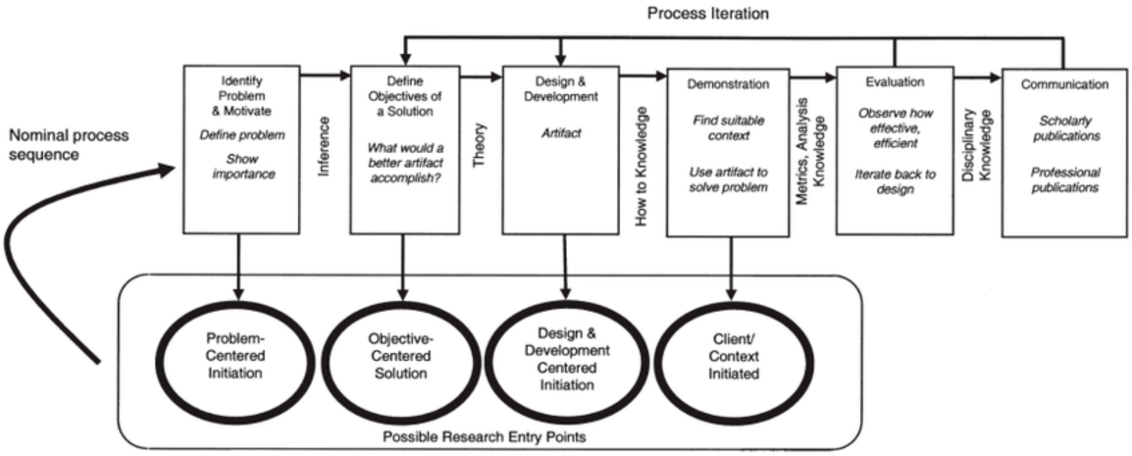

Figure 3.1: DSRM Process Model (Peffers et al., 2007).

Therefore, the DSRM model offers a structured and rigorous approach that guides the development of innovative solutions and their application in organisational contexts, ensuring practical relevance and methodological rigor.

3.1 Problem Definition and Motivation

According to the Figure 3.1 , the first step, problem identification and motivation, consists of analysing the issues that need to be resolved and their impact on the organisation. The problem must be well understood so that an effective solution can be developed. This stage establishes the foundations for the following phases, ensuring that the research addresses relevant issues that can be solved in a practical and innovative way.

To better understand the problem and justify the proposed solutions, a qualitative approach was employed, centered on semi-structured interviews with employees from the Planning and Management Control Department. This method, characterised by open-ended questions and a flexible format, enabled participants to share in-depth insights about their roles and experiences. These insights formed the foundation for defining targeted, relevant objectives for the development of the solutions.

3.1.1 Semi-structured Interviews

The semi-structured interviews were conducted based on a previously prepared script, presented in the appendix A.1. This script covers key interview topics, including interviewee identification, detailed tasks description, key challenges faced, opportunities for improvement and final questions. Interviews were conducted with all employees within the department.

To ensure the authenticity and quality of the responses, the interviews took place in person, encouraging interviewees to share their experiences openly. Sessions were recorded using audio and video recording tools such as Microsoft Teams. Additionally, detailed notes were taken to allow for accurate documentation of responses. The recordings were subsequently transcribed to support a structured and detailed analysis of the collected data.

This method, characterised by open-ended questions and a flexible format, enabled participants to provide in-depth insights into their roles and daily experiences. The conversational nature of the interviews allowed the emergence of rich and nuanced perspectives, particularly regarding the challenges they face and the tasks they consider most critical.

3.1.2 Thematic Analysis

After recording, the data were organised and analysed using NVivo, a software specialised in qualitative analysis. NVivo enables the exploration of unstructured data such as text, audio, video, images and qualitative responses from interviews. Additionally, NVivo facilitates data coding and supports various analysis techniques, like thematic analysis, which will be applied in this study.

Thematic analysis was chosen as it is a flexible approach that can be applied to different types of qualitative data. Furthermore, it allows to explore and organise data systematically, helping to identify important themes to achieve the objectives of this study. It is a simple methodology to apply, but at the same time effective in ensuring that the findings are clear and well-founded.

A thematic analysis was carried out using the steps indicated by Braun and Clarke (2006). This qualitative methodology is used to analyse unstructured data, primarily originating from interviews, focus groups and other qualitative texts. In addition, this analytical technique allows the identification of patterns (or themes) within the data, providing a deeper understanding of participants' experiences and perceptions.

Following the steps proposed by Braun and Clarke (2006), thematic analysis was structured in six steps: familiarisation with the data, coding, search for themes, review, definition of themes and production of the report. These steps, applied to our study, are presented in detail in Table 3.1, which facilitates a clear understanding of the process adopted.

Phase	Description of the process
1. Familiarising yourself with your data:	Transcribing data (if necessary), reading and re-reading the data, noting down initial ideas.
2. Generating initial codes:	Coding interesting features of the data in a systematic fashion across the entire data set, collating data relevant to each code.
3. Searching for themes:	Collating codes into potential themes, gathering all data relevant to each potential theme.
4. Reviewing themes:	Checking if the themes work in relation to the coded extracts (Level 1) and the entire data set (Level 2), generating a thematic 'map' of the analysis.
5. Defining and naming themes:	Ongoing analysis to refine the specifics of each theme, and the overall story the analysis for each theme.
6. Producing the report:	The final opportunity for analysis. Selection of vivid, compelling extract examples, final analysis of selected extracts, relating back of the analysis to the research question and literature, producing a scholarly report of the analysis.

Table 3.1: Phases of thematic analysis, according to Braun and Clarke (2006).

In this study, a thematic analysis was conducted using an inductive approach, allowing themes to emerge directly from the participants' responses without the imposition of predefined categories. This enabled a rich, data-driven interpretation that revealed both transversal challenges across the team's functions and the recurrence of specific critical tasks. The identified tasks were categorised according to their periodicity, distinguishing between monthly and annual tasks. To clearly represent these findings, Figure 3.2 illustrates the hierarchy between the main challenges and the critical tasks, organised in a visual structure that distinguishes them by type and frequency. This visual mapping facilitates the understanding of how the key issues relate to specific responsibilities within the department.

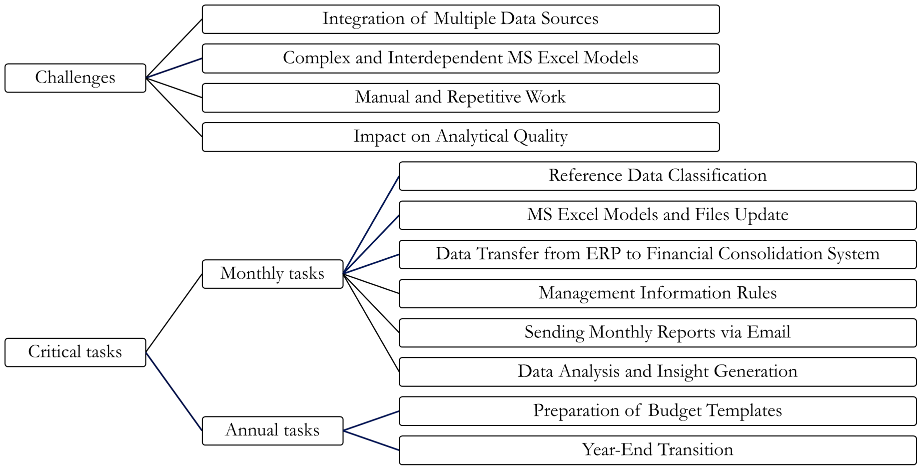

Figure 3.2: Hierarchy of Challenges and Critical Tasks.

Thematic analysis of the interviews revealed several cross-cutting challenges affecting the tasks performed by the team. These challenges hinder efficiency, compromise the quality of analytical work and reduce agility in internal processes. The main challenges identified include:

- **Integration of Multiple Data Sources:** Information is scattered across different systems and formats, which makes data consolidation and analysis complex. As management information is based on different operational systems, its production involves manual collection and validation from multiple sources, increasing not only the effort, but also the risk of errors;
- **Complex and Interdependent Microsoft (MS) Excel Models:** A complex network of interconnected MS Excel files was identified. In this informal architecture, changes in one file often affect multiple others, creating maintenance difficulties and limiting traceability;
- **Manual and Repetitive Work:** Many tasks are still performed manually, consuming significant time and exposing processes to human error;
- **Impact on Analytical Quality:** Time pressure and high operational workload limit the team's ability to conduct value-added analyses;

These challenges form the basis for defining the solution objectives and will later serve to evaluate the potential impact of the proposed improvements. Among the identified challenges, manual and repetitive work was unanimously cited by all team members (100%), indicating its widespread recognition as a critical issue. This was followed by difficulties in integrating multiple data sources and reliance on complex and interdependent MS Excel models, each mentioned by 89% of participants. In contrast, concerns related to the impact on analytical quality were raised by 44% of respondents, and these were predominantly highlighted by team leaders rather than operational staff. These results are illustrated in Figure 3.3, which presents the percentage of participants who mentioned each challenge.

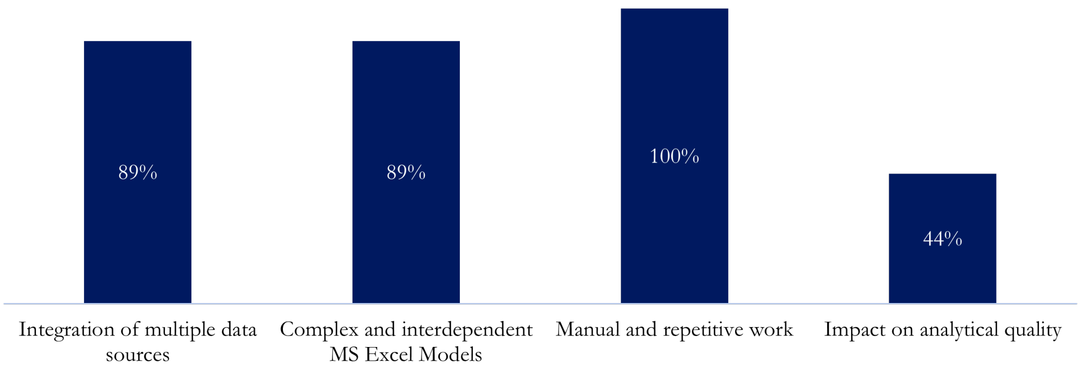

Figure 3.3: Frequency of challenges identified in interviews.

Futhermore, thematic analysis also enabled the identification of a set of critical tasks, defined as those with a high frequency of execution, substantial operational impact or elevated complexity. These tasks are central to the functioning of the Planning and Management Control Department and often demand significant manual effort and cross-functional coordination. To better understand their nature and associated challenges, tasks were grouped based on their execution frequency, distinguishing between monthly and annual responsibilities.

The monthly critical tasks are characterised by their repetitive nature and operational importance. They require significant time investment and are often performed under tight deadlines, increasing the likelihood of errors and affecting the agility of decision-making processes.

Through thematic analysis, this study identified the following critical tasks performed on a monthly basis:

- **Reference Data Classification:** The classification of reference data corresponds to the update of business intelligence hierarchies of core dimensions and attributes, such as products, services, campaigns, costs centers, financial accounts, into standardised categories. This enables consistency across systems, supports accurate reporting and facilitates effective data integration and analysis;

- **MS Excel Models and Files Update:** Each month, several management information models, based on multiple MS Excel files must be updated to incorporate the most recent data. This process involves collecting information from various sources, entering it into the appropriate worksheets and refreshing the models to reflect the current reporting period;

- **Data Transfer from ERP to Financial Consolidation System:** This task involves selecting the appropriate parameters within ERP system, extracting the relevant data, and transferring it to Financial Consolidation System for subsequent analysis and reporting. This process ensures that the data is correctly aligned and available for accurate financial management;

- **Management Information Rules:** After the ERP data is loaded to the Financial Consolidation System, manual management information rules are subsequently required. These adjustments are executed in MS Excel and correspond to business intelligence rules that refine and compose the Financial Consolidation information (retrieved through an MS Excel add-in). The adjusted dataset is exported in CSV format, reformatted using a text editor software and ultimately re-imported into the Financial Consolidation System;

- **Sending Monthly Reports via Email:** Monthly reports, such as the Profit & Loss statement (P&L), are shared via email. This task involves selecting and attaching the appropriate files, composing the email content in accordance with the reported data and verifying that the distribution list is accurate. This process ensures accurate and timely dissemination of financial information to relevant stakeholders;

- **Data Analysis and Insight Generation:** Data from the prepared MS Excel models are processed to generate comprehensive reports and MS PowerPoint presentations. Additionally, the data is analysed to extract actionable insights from the business performance review, supporting decision-making and contributing to strategic planning;

In contrast to the monthly tasks, annual critical tasks tend to involve broader updates and preparations that require intensive manual work over a shorter period. Although less frequent, these tasks have a high impact on planning processes and are often critical for ensuring operational readiness for the new fiscal year.

- **Preparation of Budget Templates:** The preparation of the annual budget consists of updating MS Excel data models with historical data and assumptions to project future financial outcomes. This process ensures that all necessary financial parameters are accounted for, providing a structured basis for strategic decision-making;

- **Year-End Transition:** The transition into a new fiscal year involves updating MS Excel data models to reflect the new time frame, including the addition of new columns and rows, delete of old columns and rows and the review of formulas that reference external files or data ranges. This ensures that the data remains accurate and aligned with the updated fiscal calendar;

The Figure 3.4 presents the percentage of participants who mentioned each task, calculated based on the number of individuals who actually perform that specific task. This analysis aims to assess the degree of perceived relevance or salience of each activity among those directly involved in its execution. Notably, all participants who are responsible for Data Transfer from ERP to the Financial Consolidation System explicitly mentioned it during the interviews, resulting in a 100% mention rate. Other tasks with high levels of recognition include Reference Data Classification, MS Excel Models and Files Update, and Data Analysis and Insight Generation, each mentioned by over 75% of those who perform them.

In contrast, certain critical tasks, such as the Preparation of Budget Template and Year-End Transition, were referenced by a smaller proportion of participants, despite being performed by all department members. A plausible explanation for this discrepancy is the timing of the interviews, which did not coincide with the execution of these tasks, potentially reducing their salience during the interviews and leading participants not to recall or prioritise them in their responses.

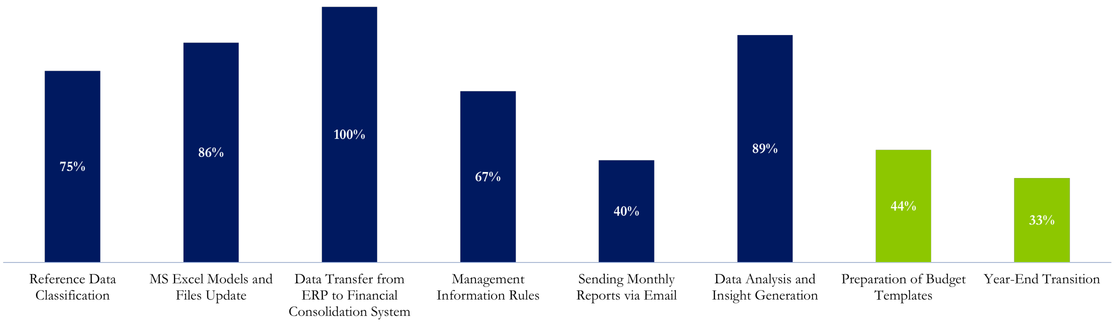

Figure 3.4: Percentage of task performers who mentioned the task as critical.

Following the identification of the most critical tasks, a subsequent analysis examined the distribution and relative contribution of each challenge to the execution of these tasks. Figure 3.5 illustrates this by depicting each critical task as a segmented bar, where the segments represent the percentage contribution of different challenges within that task. This format provides a clear visualisation of the dominant difficulties associated with each process.

The analysis reveals that several tasks are predominantly manual in nature, such as Sending Monthly Reports via Email and Reference Data Classification, where manual and repetitive work constitutes nearly the entire challenge profile. More broadly, manual and repetitive work emerges as the most pervasive challenge across the majority of tasks. Notably, the task MS Excel Models and File Updates stands out as the only one to encompass all identified challenges, highlighting its particular complexity and the multifaceted difficulties it presents.

These insights underscore the critical impact of manual processes on operational efficiency and the heightened risk of errors, especially in tasks requiring extensive data handling and integration from multiple sources.

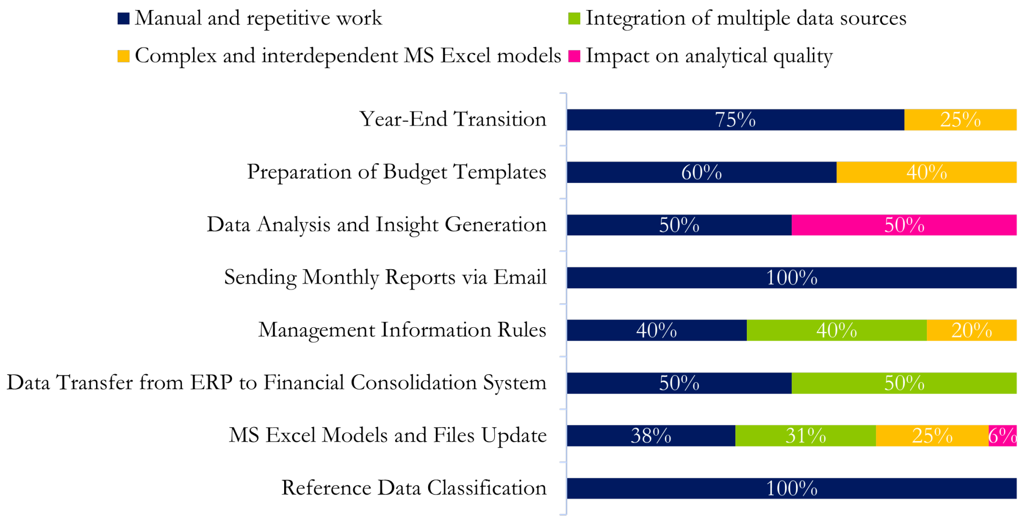

Figure 3.5: Distribution of challenges associated with each task.

In summary, the thematic analysis provided a comprehensive overview of the critical tasks and recurring challenges experienced across teams. The findings highlight not only the operational complexity and fragmentation of current processes, but also the limitations imposed by excessive manual work, data dispersion and the lack of integrated systems. These insights offer a solid foundation for defining the objectives of a potential solution.

3.2 Definition of the Objectives

After identifying and analysing the core challenges and critical tasks faced by the Planning and Management Control Department in Phase I, the next step in the Design Science Research Methodology (DSRM) involves defining the objectives that the proposed solution should achieve. This phase marks a shift from understanding the problem to outlining what a successful solution must accomplish. It provides a structured framework for guiding the development of technological artifacts that are both practically relevant and theoretically grounded.

In this context, the definition of solution objectives involves setting clear, measurable and realistic goals that articulate what an effective artifact should deliver, the results it should produce and the benefits it is expected to bring. These objectives not only shape the development process, but also establish the criteria by which the artifact will later be evaluated, ensuring its alignment with the identified problems and organisational needs.

The definition of these objectives was grounded in the diagnostic data gathered during Phase I, with particular attention to:

- The most frequently mentioned challenges during interviews;
- The critical tasks with the highest impact and recurrence;
- The operational and technological context of the team;

3.2.1 Solution Objectives

Building on the diagnostic findings presented in the previous chapter, which highlighted the key operational challenges and the most critical and time-consuming tasks, this section outlines the objectives that the proposed solutions must achieve. These objectives are central to ensuring that any future technological interventions are aligned with the real objectives of the Planning and Management Control Department. Specifically, the solution should aim to increase operational efficiency, reduce the time spent on routine and low-value tasks that consume substantial resources and enable the team to focus more on generating strategic insights rather than performing repetitive manual work.

It is important to note that the solution proposed in this study is not intended for immediate implementation. Instead, it aims to present potential technological alternative solutions, which can inform and guide future development initiatives. With this in mind, the following objectives were defined to guide the design and evaluation of the proposed solutions:

- **Reduction of execution time for critical tasks:** Minimise the time spent on high-frequency operational tasks, especially those characterised by a high degree of manual and repetitive effort;

- **Reduction of redundant or unnecessary files:** Streamline the current network of interdependent MS Excel files by promoting a simplified and more robust information architecture that reduces redundancy and enhances data traceability;

- **Preservation or improvement of output quality:** Ensure that the adoption of technological solutions does not compromise, but ideally improves, the reliability of data, the accuracy of analyses and the consistency of the financial outputs produced by the team;

- **Reduction of solution production and maintenance costs:** Propose technologically viable and economically sustainable solutions, whose implementation and ongoing maintenance costs are compatible with the budgetary and resource constraints of the organisation;

These objectives serve not only as a conceptual guide for the design of potential solutions, as a foundation for their systematic evaluation. In order to assess the extent to which these objectives could be achieved in practice, a set of specific and measurable metrics were defined, which are intended to support future decision-making by enabling the comparative assessment of alternative technological proposals.

3.2.2 Metrics for Evaluating Objectives

Building on the objectives outlined in the previous chapter, which were established to address the identified challenges, this section defines the metrics that were used to evaluate the potential solutions. These metrics were designed to assess the extent to which the proposed technological alternatives can meet the defined objectives.

It is important to note that the evaluation of these solutions relied on estimated data, as the actual implementation and real-world testing of the solutions fall outside the scope of this study. For example, while we can estimate the time spent on critical tasks prior to the proposed solutions, the actual time savings post-implementation can only be approximated based on insights gained from interviews and expert estimates.

The following five metrics served as the primary tools for evaluating the potential impact of the solutions, providing a foundation for their future application and validation:

- Metric 1: Time savings;
- Metric 2: Number of removable files;
- Metric 3: Output quality;
- Metric 4: Cost of development and maintenance;
- Metric 5: Return on Investment (ROI) assessment;

3.2.2.1 Metric 1: Time savings

This metric aims to identify the critical tasks that consume the most time, providing valuable insights into the key operational bottlenecks within the Planning and Management Control Department. Data collection were performed using an MS Excel spreadsheet, which were completed daily by team members throughout a period of one month. This spreadsheet, which is included in the the appendix A.2, serverd as the primary tool for capturing essential task-related information. For each task executed, the following details should be documented:

- The task performed;
- The start and end times of the task execution;
- The person responsible for carrying out the task;
- The specific process to which the task belongs;

By systematically recording this data, it was possible to calculate the total accumulated time spent on each type of task. This allowed for a comprehensive analysis of time distribution across different activities, enabling the identification of tasks that consume the most time. Furthermore, this information facilitated the identification of operational bottlenecks, pinpointing areas where inefficiencies may exist. Such insights were instrumental in prioritising tasks that have the greatest potential for automation or process improvement. Ultimately, the data collected supported more informed decisions regarding resource allocation and the strategic implementation of future solutions aimed at optimising team performance.

3.2.2.2 Metric 2: Number of Removable Files

This metric was developed to assess the structural complexity and redundancy within the complex MS Excel models, which is heavily reliant on interdependent MS Excel spreadsheets. The overreliance on such files not only increases the risk of errors and inconsistencies, as also contributes to operational inefficiencies and difficulties in maintaining data integrity across processes. Consequently, this metric seeks to identify opportunities to simplify the file architecture by detecting files that may be considered redundant or replaceable through technological automation.

To achieve this, a Python script was developed to analyse the directory structure and extract key information about file dependencies. The script performs an automated scan of MS Excel and MS PowerPoint files within a specified folder, identifies inter-file links, including formula references and embedded objects and constructs a table that maps the dependencies among documents, effectively capturing the “file chain” relationships. Based on this data, a directed network graph is generated, where each node represents a file and edges indicate dependency relationships. This visual representation provides a clear overview of the system's complexity.

To enhance the interpretability of the network, a clustering algorithm was applied to group files into distinct clusters based on their interconnectivity, typically corresponding to specific processes or functional areas. This approach not only highlights the concentration of dependencies within certain parts of the system, but also helps to identify long chains of intermediary files that could potentially be eliminated or replaced by integrated solutions, such as a centralised MS Power BI dashboard connected directly to databases.

A file is considered removable if it serves solely as an intermediary, meaning it is neither a data source nor a final output, and/or if its function can be replicated through automation. However, due to organisational constraints, implementing the automated script was not feasible within the scope of this study. Specifically, access restrictions to shared team folders, combined with the risk of disrupting existing workflows and information flows, limited the possibility of deploying automated scanning in the live environment. As a result, the review of the file structure and identification of redundant or unnecessary files was conducted manually, based on the judgment of team members responsible for the associated processes. Their contextual knowledge ensured that any proposed simplifications remained aligned with operational realities. An illustrative example of the resulting network graph, with files visually grouped by cluster, is presented in annex A.3, showcasing the application of this methodology and its potential for uncovering structural inefficiencies in file-based processes.

The output of this analysis supports the quantification of removable files, enables a clearer understanding of systemic complexity and facilitates the identification of automation opportunities that would have the highest impact.

3.2.2.3 Metric 3: Output Quality

This metric evaluates the quality of the outputs generated by the proposed solutions, aiming to verify whether they are capable of replicating or enhancing the results traditionally produced through manual processes. It ensures that technological automation does not compromise the reliability, accuracy or usability of the outputs considered critical by the Planning and Management Control Department.

For Machine Learning-based solutions, the evaluation involves training models on historical datasets and subsequently applying them to new data. The outputs generated by the model are compared against manual results, which serve as the standard reference. In this case, accuracy was adopted as the primary indicator, representing the percentage of correctly predicted or classified outcomes relative to the manually produced benchmark.

While the evaluation of ML-based solutions was grounded in objective performance metrics such as accuracy, the assessment of other tool-based outputs emphasises subjective user perceptions. Together, these approaches provide a holistic view of output quality across different technological contexts.

Therefore, for other types of solutions, such as those based on tools like MS Power BI, a qualitative indicator called the output quality score was employed. This score reflects the degree of alignment between the automated output and the expected manual result. Besides that, it is constructed based on users' perceptions of the automated output, typically grounded in satisfaction levels observed during pilot testing or demonstrations of prototype solutions. Since the solutions were not implemented in this study, all quality assessments were estimated and validated through interviews with key team members responsible for the affected tasks.

The evaluation methodology was based on the Information Quality dimensions proposed by Sedera and Gable (2024) in their validated framework for assessing Enterprise System success. Six key dimensions were selected for inclusion in the analysis: availability, usability, understandability, relevance, format, and conciseness. These dimensions are well-established in the literature and provide a comprehensive lens through which the perceived quality of outputs can be systematically evaluated.

To operationalise this metric, a structured questionnaire was designed (included in Appendix A.4), targeting team members responsible for the tasks associated with the outputs under analysis. It was presented with a prototype and asked to rate it on a Likert scale from 1 (very poor) to 5 (excellent) across the six information quality dimensions. The items assessed were:

- **Availability:** The extent to which the output is accessible in a timely manner when needed for decision-making;
- **Usability:** The ease with which the user can interact with and utilise the output in practice;

- **Understandability:** The degree to which the information is clear, well-organised and easy to interpret;
- **Relevance:** The usefulness and appropriateness of the content in supporting the user's specific work tasks;
- **Format:** The adequacy of the visual and structural presentation of the data (e.g., charts, tables, layouts);
- **Conciseness:** The extent to which the information is communicated efficiently, without unnecessary complexity or overload;

The output quality score is calculated as the simple arithmetic mean of the six dimension scores provided by the element of team involved in the execution of the task. This score, ranging from 1 to 5, serves as a qualitative estimate of the overall perceived quality of the output and enables direct comparison across different types of proposed solutions. In the absence of full implementation, this approach offers a structured and theory-driven way to estimate impact based on expert user judgment.

Each dimension in the questionnaire was assessed using a 5-point Likert scale, which allowed respondents to express their level of agreement or satisfaction with each quality attribute of the proposed output. The scale was defined as follows:

- **1 – Very Poor:** The output fails to meet expectations in this dimension and is considered unsuitable for practical use;
- **2 – Poor:** The output demonstrates significant shortcomings that impair its usefulness or clarity;
- **3 – Acceptable:** The output meets minimum expectations but includes notable limitations or areas for improvement;
- **4 – Good:** The output performs well in this dimension, with only minor deviations from optimal quality;
- **5 – Excellent:** The output fully meets or exceeds expectations, offering a high-quality, reliable alternative to manual processes;

This scale ensures consistency in data collection and interpretation, enabling meaningful comparisons across different outputs and user evaluations. By quantifying subjective assessments, it provides a practical way to estimate output quality in the absence of large-scale implementation.

By combining a validated theoretical model with a structured qualitative assessment method, this metric not only ensures methodological rigor, but also provides practical insights to guide future implementation efforts.

3.2.2.4 Metric 4: Cost of Development and Maintenance

This metric aims to evaluate the economic feasibility of each proposed technological solution, ensuring that the decision-making process is informed by a realistic understanding of the resources required. The goal is to support the prioritisation of initiatives that maximise value while minimising unnecessary expenditures, especially in budget-constrained environments such as corporate planning and control.

Although the solutions under consideration have not yet been implemented, the metric is structured to allow for a consistent and comparative estimation of the investment needed for each. The cost estimation framework comprises three primary components:

- **Human Resources:** refers to the estimated effort required for the design, development, testing and deployment of each solution. This includes the number of working hours from analysts, developers or other relevant professionals, multiplied by standard internal cost rates. The estimate accounts for the complexity of the solution and the level of customisation required;
- **Software Licensing:** captures potential expenditures associated with the use of proprietary tools or platforms. Examples may include MS Power BI Pro or Premium licenses, RPA platforms such as UiPath or Power Automate, and any specialised software or libraries that require paid access or subscriptions;
- **Infrastructure and Technical Support:** encompasses anticipated costs related to integration with existing systems (e.g., ERP system and Financial Consolidation System) and the future need for system maintenance, technical support and potential updates. This component reflects both initial implementation overheads and recurring operational costs;

This metric were applied uniformly across all proposed solutions and were synthesised into a comparative table (to be presented in a later chapter). While the values assigned to each cost component are preliminary and based on expert judgment, they offer a credible foundation for evaluating the relative financial impact of each solution.

By explicitly considering development and maintenance costs at this stage, the analysis ensures that technical recommendations are grounded in financial reality, contributing to a balanced assessment of each proposal's overall value.

3.2.2.5 Metric 5: Return on Investment (ROI) Assessment

This metric was designed to assess the long-term financial viability of each proposed solution by estimating its Return on Investment (ROI) over a five-year horizon. The goal is to incorporate an economic dimension into the evaluation framework, ensuring that proposed solutions are operationally effective and financially justifiable.

The ROI metric aims to quantify the expected return generated by each solution relative to its estimated cost of development and maintenance. It serves as a decision-support tool by identifying the break-even point, the moment when accumulated financial benefits exceed the total investment and by illustrating how value is accrued over time.

To structure this analysis, the ROI for each solution were calculated over a five-year period, taking into account both the total estimated costs and the projected financial benefits.

The total estimated costs are derived directly from metric 4, which outlines the estimated cost of development and maintenance. These costs encompass various components, including the development time required for each solution, the costs associated with software licensing (e.g., MS Power BI, RPA tools), infrastructure integration, ongoing support and maintenance.

On the other hand, the financial benefits of the solution are primarily driven by the estimated productivity gains captured in metric 1, time savings. The time savings quantifies the number of labor hours saved through the automation of manual processes or the optimisation of existing workflows. These saved hours are then converted into monetary value using standardised internal cost rates, reflecting the average cost of the personnel involved in the relevant tasks.

This calculation allows for a comprehensive view of the financial impact of each solution, considering both initial implementation costs and long-term savings. While these figures are based on estimates, they provide a solid foundation for decision-making, based on current knowledge and expert input.

By incorporating the ROI metric, this evaluation framework not only captures the operational efficiency and effectiveness of the proposed solutions, but also ensures that their long-term economic sustainability is properly assessed. This holistic approach provides valuable insights into the feasibility and value of each proposed technological solution, supporting the decision-making process for selecting the most appropriate option based on both performance and cost-effectiveness.

Chapter 4

Design and Development

The design and development stage refers to the creation of the artifact that will be used to solve the problem. The construction of the artifact is guided by iterative design principles, allowing for continuous adjustments and improvements during the development process. This step ensures that the artifact is adapted to meet the identified objetives, being adjusted as new insights emerge throughout the design process.

Therefore, in this study, this phase focused on identifying solutions to address the critical tasks and challenges faced by the Planning and Management Control Department. These tasks were derived from the thematic analysis conducted in Phase I, which revealed several inefficiencies and operational bottlenecks. Based on the findings from this analysis and aligned with the objectives defined in Phase II, tailored solutions were designed to address these challenges. The solutions proposed aimed to mitigate the challenges identified, improving overall efficiency and performance within the department.

This phase incorporates both non-AI solutions and AI-driven solutions. While the core focus of this research lies in the application of Artificial Intelligence, it became apparent through the interviews and analysis that the majority of the challenges faced by the department were linked to operational and repetitive tasks with a high degree of manual labor. As such, it was found that introducing automation solutions without AI, primarily leveraging Robotic Process Automation, would have a more immediate impact and broader applicability in addressing these operational inefficiencies.

Consequently, the solutions were categorised into two groups: non-AI-based solutions and AI-based solutions. This distinction ensures that the proposed solutions are aligned with the objectives of the department, addressing both low-complexity tasks that benefit from basic automation, and high-complexity tasks that require more sophisticated AI methods. Despite the central focus on AI, the analysis revealed that the bulk of inefficiencies stemmed not from the lack of AI, but from the absence of basic process automation. As a result, prioritising non-AI automation solutions became essential. However, AI was proposed when the task complexity and data volume justified its adoption.

4.1 Proposed Solutions

The solutions proposed in this phase were directly aligned with the critical tasks identified in the earlier analysis. The tasks addressed encompass both non-AI-based and AI-based solutions. Below, it is provide a detailed explanation of the critical tasks, the problems they present, the solutions proposed and the objectives set for each solution.

4.1.1 Non-AI-Based Solutions

4.1.1.1 Management Information Rules

Management Information Rules are a critical component of the financial reporting process, ensuring that data accurately reflects the financial reality of the organisation after initial loading. This task involves post-processing operations to correct or supplement data according to specific accounting or managerial requirements. As currently implemented, the Management Information Rules workflow is highly manual. Once the ERP data has been loaded into the Financial Consolidation System, the process requires a series of manual interventions carried out in MS Excel. These interventions apply business intelligence rules to refine and shape the data extracted via an MS Excel add-in. Following these adjustments, the dataset is exported as a CSV file, undergoes reformatting through a text editor software to comply with system requirements, and is then re-imported into the Financial Consolidation System for final processing.

This process illustrates three of the key challenges identified in the thematic analysis: manual and repetitive work, the integration of multiple data sources and complex and interdependent MS Excel models. Each adjustment cycle requires significant user input, repetition of low-value tasks, close attention to formatting and data consistency across platforms. The need to alternate between MS Excel, the text editor software and the Financial Consolidation System introduces complexity and inefficiencies, as well as a heightened risk of human error and inconsistencies, which can compromise data quality and delay financial closing activities. Additionally, the manual nature of the task reduces the time available for value-added activities such as validation, analysis or strategic reporting.

To overcome these limitations, two alternative solutions are proposed. The first involves leveraging on native rule implementation directly within the Financial Consolidation System. By configuring these rules to automatically apply predefined adjustments during the data loading or consolidation phases, the need for external data transformation is eliminated. This approach ensures higher consistency, reduces operational risks and enhances auditability.

Alternatively, in cases where system limitations or organisational policies restrict direct rule-based automation in the Financial Consolidation System, a second solution is proposed through Robotic Process Automation. In this approach, an RPA system would replicate the current manual workflow, extracting data, performing transformations in MS Excel, formatting the output in the text editor software and reimporting it into the Financial Consolidation System. This end-to-end automation would significantly reduce the burden on human resources while maintaining compatibility with the existing process architecture.

Ultimately, the objective of both solutions is to automate the Management Information Rules process, thereby improving operational efficiency, reducing manual errors, promoting more reliable and timely financial reporting. The choice between the two depends on technical feasibility, internal governance and budget constraints.

4.1.1.2 MS Excel Models and Files Update

One of the most time-consuming and error-prone activities identified during the thematic analysis is the monthly update MS Excel models and files update used for reporting and monitoring purposes. This task consists of collecting new data from diverse internal sources, manually inputting it into structured spreadsheets, and ensuring that all formulas and references are correctly updated to reflect the current reporting period. This process is central to the department's information flow and directly impacts the accuracy and timeliness of the insights generated for decision-making.

This task is particularly affected by four major challenges: manual and repetitive work, integration of multiple data sources, complex and interdependent MS Excel models, and the resulting impact on analytical quality. The manual nature of the updates introduces a significant risk of human error, especially as multiple datasets must be reconciled across numerous tabs and linked workbooks. The constant copying of data from the several ERP systems or other sources to MS Excel files consume valuable time. Furthermore, the absence of a centralised system capable of dynamically integrating new data contributes to fragmentation, undermining both the coherence and the reliability of the reports produced.

To address these challenges, the proposed solution is the implementation of MS Power BI as a central reporting and automation tool. MS Power BI offers the ability to connect directly to multiple data sources, including MS Excel files, SQL databases and ERP systems. Once integrated, the data may be refreshed automatically, eliminating the need for manual updates and potentially reducing the risk of formula errors. Additionally, by using parameterised queries and dynamic date filters, MS Power BI has the potential to automatically shift reporting periods without the need to adjust formulas or duplicate workbooks each month.

This solution is expected not only to optimise the update process, but also enhance the quality of analysis by ensuring that data is always current, correctly linked and presented in a consistent format. By reducing dependency on interlinked MS Excel files, it could improve system robustness and decreases the time analysts spend on routine maintenance, freeing them to focus on more strategic activities. Ultimately, the objective is to automate the monthly file update process, thereby improving efficiency, enhancing data quality and ensuring faster and more reliable delivery of insights to stakeholders. However, the extent to which this solution addresses all processes is subject to further evaluation and may vary depending on specific operational constraints.

4.1.1.3 Sending Monthly Reports via Email

The sharing of the monthly reports is a critical monthly task within the Planning and Management Control Department. It involves identifying the correct financial files, preparing the accompanying message based on the results reported, verifying the email content and ensuring that the correct distribution list is used. Although operational in nature, this process is essential to maintaining consistent communication with stakeholders across the organisation, guaranteeing that timely and accurate financial information is shared for review and decision-making.

As evidence in thematic analysis, this task is heavily affected by manual and repetitive work. The current method requires users to manually select and attach multiple reports stored across several folders. Furthermore, the manual nature of the email preparation and dispatch significantly increases the potential for oversight, such as sending outdated files, composing incorrect messages or using incomplete recipient lists.

To address these inefficiencies, the proposed solution involves the development of an RPA system capable of managing the end-to-end process. This system would monitor a predefined folder, detect when the latest versions of the reports are available, automatically compose and send the corresponding emails. The bot would retrieve email addresses from a master list, attach the appropriate files and generate dynamic email content based on a predefined template linked to the financial results. This automation ensures consistency, reduces human error and saves considerable time in a task that, even though is a routine, is fundamental to operational transparency.

The main objective of implementing this RPA-based solution is to eliminate the manual steps involved in sending monthly reports, ensuring greater accuracy, efficiency and traceability in the communication process.

4.1.1.4 Data Transfer from ERP to Financial Consolidation System

The extraction of financial data from ERP and its subsequent transfer to Financial Consolidation System is a recurring and essential task within the monthly financial reporting process. This operation involves selecting specific parameters in the ERP system, exporting the relevant datasets and preparing them for accurate upload into the Financial Consolidation System. The data transferred through this workflow supports consolidation, variance analysis and other key financial management activities.

However, as identified in the thematic analysis, this task is currently executed in a highly manual and fragmented manner, giving rise to two critical challenges: manual and repetitive work and integration of multiple data sources. The reliance on manual extraction and formatting not only introduces inefficiencies, but also increases the risk of error, delays and inconsistencies. Users are required to manually navigate ERP interfaces, extract data to MS Excel files, apply formatting rules and finally upload the processed data into the Financial

Consolidation System, often through intermediary tools, such as a text editor software.

To address these limitations, two complementary solutions have been considered. The first involves the implementation of a predefined connector between the ERP and the Financial Consolidation System, which is already available on the market, but not yet adopted by the organisation. This connector would enable direct and automated integration between the two systems, eliminating the need for manual intervention during data extraction and upload. Its implementation would significantly improve data alignment, streamline the monthly reporting cycle and enhance overall system interoperability.

As an alternative or an interim solution in cases where immediate connector implementation is not feasible, the development of a RPA system is proposed. This RPA bot would replicate the current manual workflow, including logging into the ERP system, selecting parameters, exporting data, reformatting files and importing the results into the Financial Consolidation System. While more limited in scalability compared to a native connector, this solution provides a practical and flexible way to reduce human workload and mitigate the risks associated with manual data handling.

In both scenarios, the goal is to improve efficiency, data integrity and process reliability. Automating the ERP-to-Financial Consolidation System data transfer not only ensures more timely and accurate reporting, but also allows financial analysts to focus on tasks of greater strategic value, such as insight generation and performance review.

4.1.1.5 Preparation of the Budget Templates

The annual preparation of the budget templates plays a central role in supporting the organisation's financial planning and strategic alignment. Traditionally, this task relies on the manual extraction and consolidation of historical data across multiple periods into MS Excel templates. These files are then distributed to various business areas, which use them to estimate future operacional and financial performance and define budgetary targets for the upcoming fiscal year.

This approach, while familiar, presents several operational inefficiencies that were highlighted during the thematic analysis, most notably, the complex and interdependent MS Excel models and the manual and repetitive nature of the work involved. The process of copying and structuring data from different time periods into separate templates not only consumes valuable time, as introduces risks of inconsistency, formula errors and loss of data integrity due to broken references and version control issues. As a result, the quality and reliability of the financial planning process are compromised and the effort required from the team is significantly increased.

To mitigate these challenges, the proposed solution leverages MS Power BI as a data integration and analysis tool to support a more efficient and controlled budgeting process. Rather than relying solely on MS Power BI for budget input, the approach focuses on using the platform to extract, consolidate and visualise historical data directly from source systems. These structured datasets are then exported into MS Excel, where automated procedures, implemented through macros or RPA, format the files and incorporate the necessary columns for future periods, as well as summary indicators.

This approach has the potential to simplify the preparation of budget templates by improving data consistency while maintaining the flexibility for business units to complete their forecasts within a familiar MS Excel environment. In doing so, the solution is expected to enhance the efficiency, transparency and traceability of the budgeting cycle without disrupting existing workflows.

By reducing manual intervention and ensuring access to accurate and up-to-date information, the proposed approach may improve both the efficiency and the reliability of the budget preparation process, contributing to more robust financial planning and informed strategic decision-making across the organisation.

4.1.1.6 Year-End Transition

The transition into a new fiscal year is a recurring yet labour-intensive process that involves systematically updating a wide range of MS Excel files to align with the new reporting calendar. This typically includes the insertion of columns for the new year, removal of obsolete ones and adjustment of formulas, many of which reference external sources or rely on interdependent structures. These actions are crucial to ensure that all financial reports and analytical tools continue to operate correctly and reflect accurate and current-period data.

However, this task embodies two of the central challenges highlighted during the thematic analysis: the manual and repetitive nature of the work and the complex and interdependent MS Excel models. Because many of these templates have evolved organically over time, they often contain complex linkages and dependencies that are vulnerable to error during manual updates. Even a small oversight in formula adjustment or data linkage can compromise the integrity of downstream reports and introduce delays in the financial closing process. Moreover, the manual effort required for this transition diverts skilled resources from higher-value analytical work.

To mitigate these inefficiencies, the proposed solution involves the development of a centralised data model in MS Power BI. This platform supports the creation of dynamic reporting templates that may automatically adjust to the fiscal year based on predefined time parameters. Rather than reconfiguring multiple individual MS Excel files each year, users interact with a unified system where the fiscal time frame is controlled centrally, thereby potentially reducing the administrative burden associated with the year-end transition. Additionally, MS Power BI enables direct integration with multiple data sources such as ERP systems, SQL Server and MS Excel, ensuring that updates are propagated consistently and in real time across the reporting architecture.

This approach is expected to reduce the manual effort required during the fiscal year transition, while improving temporal consistency and promoting greater integration across systems. By eliminating the need to manually update numerous interdependent templates, the proposed approach has the potential to streamline operations, enhance data reliability and reduce the risk of error. Ultimately, this may allow the finance team to focus more on analysis and strategy rather than administrative maintenance, fostering a more agile and accurate financial planning cycle.

4.1.2 AI-Based Solutions

4.1.2.1 Reference Data Classification

The Reference Data Classification plays a vital role in organising the Business Intelligence (BI) Hierarchies of core dimensions and attributes, such as products, services, campaigns, costs centers, financial accounts, into standardise categories. This process is crucial for maintaining consistency across systems, supporting accurate reporting and enabling effective data integration and analysis.

As evidenced in the thematic analysis, the current classification method is characterised by a high dependence on manual and repetitive tasks. This labour-intensive and time-consuming approach constitutes a significant bottleneck in the overall data preparation process. The repetitive nature of the work further results in the suboptimal allocation of human resources, diverting time and effort from more strategic and value-generating activities.

To address these issues, the proposed solution involves the application of Machine Learning-based classification methods to automate the classification of data, such as neural networks and random forest classification. By learning from historical data and recognising underlying patterns, the system would be able to identify patterns and automatically categorise the data, significantly improving both the accuracy and consistency of the classification process. This approach eliminates the need for manual intervention, thereby reducing subjectivity and the potential for errors.

The objective of this solution is to improve the accuracy and consistency of reference data classification while also reducing the time and effort involved in the process. Automating this task addresses the challenges identified in the thematic analysis by eliminating manual work and enhancing both the efficiency and reliability of data management. As a result, the expected outcome is a more reliable and efficient classification system, which will improve overall data quality and support more accurate decision-making processes. In the long term, this approach is anticipated to optimise operational workflows, minimise errors and ensure that the organisation can rely on high-quality and consistent data for its strategic decision-making.

4.1.2.2 Data Analysis and Insight Generation

The process of data analysis and insight generation is essential for transforming raw data into actionable intelligence that can support decision-making and strategic planning. In its current form, this task involves processing data extracted from prepared MS Excel files to create comprehensive reports and MS PowerPoint presentations. However, the largely manual and repetitive nature of these tasks significantly hinders operational efficiency. Such labour-intensive processes consume considerable time and resources, while diverting focus from more strategic and value-added analytical activities.

Moreover, this dependence on manual handling negatively impacts the quality of the analytical outputs. The frequent repetition of data processing increases the likelihood of errors and inconsistencies, thereby compromising the accuracy and reliability of the insights generated. Consequently, this diminishes the organisation's ability to base decisions on precise and current information.

To address these issues, the proposed solution involves the implementation of MS Power BI, a business analytics tool designed to optimise data analysis and reporting. MS Power BI enables the integration of data from multiple sources, allowing for the seamless consolidation of information in a centralised platform. This integration eliminates the need for manual data manipulation, improving the quality and consistency of the data. Moreover, MS Power BI's advanced analytical capabilities, including real-time data updates and interactive dashboards, allow for more dynamic and timely insights, supporting better decision-making and strategic planning.

Additionally, MS Power BI's Copilot functionality enhances the analysis process by enabling users to ask questions in natural language and receive instant answers and visualisations. This feature further reduces the time spent on manual tasks, allowing users to focus on higher-level analysis and the generation of actionable insights. The automation of routine tasks enhances the overall analytical quality and enables more accurate and efficient reporting.

The objective of this solution is to improve the quality and efficiency of data analysis by automating manual processes, enabling seamless data integration, and providing real-time insights. By leveraging MS Power BI, the solution aims to reduce the time spent on data preparation, eliminate errors and enhance the quality of the insights generated. This would lead to more informed, data-driven decision-making and better support for strategic planning.

Therefore, the integration of MS Power BI into the data analysis and insight generation process offers a comprehensive solution to the challenges identified in the thematic analysis. By automating manual tasks and enhancing analytical quality, this solution promises to significantly increase the efficiency of data-driven decision-making processes. Furthermore, it empowers decision-makers with timely, accurate insights, supporting more effective and strategic planning across the organisation.

4.2 Prototype Development

Following the analysis of critical tasks and the identification of underlying challenges two functional prototypes were developed as part of the design cycle. While several proposed solutions involved Robotic Process Automation, the actual prototyping effort focused on MS Power BI-based models. This decision was informed by internal constraints regarding access and authorisation for RPA development tools, which limited the scope of automation implementations.

Consequently, MS Power BI was selected as the primary platform for prototype development, given its flexibility in data modelling, strong integration capabilities and potential to reduce human intervention in data handling. The goal was to demonstrate, through two distinct, but complementary prototypes, how digital transformation in operational and financial reporting and planning could address multiple operational inefficiencies while improving data quality and strategic insight generation.

The first prototype focused on an existing operational KPIs report, selected for its representativeness and relevance in daily departmental activities. This report was particularly suitable for evaluation, as it allowed a more objective measurement of the performance metrics defined in Phase II. Its transformation into MS Power BI enabled the automation of previously manual processes, improved data reliability and facilitated quicker access to key performance indicators.

The second prototype was developed from scratch, based on a summary MS Excel file that previously served only as a static support tool. In MS Power BI, this information was redesigned into an interactive and visually engaging dashboard, enhancing user experience and enabling more intuitive exploration of the data. The goal was not only to improve aesthetic and functional aspects, but also to enable faster and more informed decision-making through a dynamic and user-centred interface.

These prototypes not only serve as practical demonstrations of the feasibility and added value of the proposed improvements, but also as the basis for evaluating the output quality (Metric 3).

4.2.1 Prototype A - Visual Report Automation Based on Existing MS Excel Templates

Prototype A was developed to replicate and enhance a commonly used MS Excel-based financial report, which typically spans multiple sheets and is manually updated each reporting cycle. The original process involved significant effort in linking numerous interdependent MS Excel files, updating formulas and manually generating narrative insights before the final output was exported to PDF and distributed to stakeholders.

To optimise and modernise this task, the MS Power BI version was constructed to mirror the visual layout and structure of the original MS Excel report, thereby maintaining user familiarity. However, unlike the original MS Excel version, the MS Power BI report sources its data directly from an integrated data model built on MS Excel files that contain data extracted from the original data sources. This approach eliminates the need for external links between MS Excel files and reduces the risk of inconsistencies or formula errors.

A further enhancement is the automation of narrative insights: where previously these were manually written each month, the new version uses Data Analysis Expressions (DAX) measures to generate dynamic textual insights based on the current reporting period. MS Power BI's Copilot functionality represents a valuable advancement. It allows users to interact with reports through natural language queries, improving both accessibility and analytical flexibility. However, implementing this feature was not feasible within the scope of this project due to licensing limitations.

This prototype directly addresses challenges related to manual and repetitive work, complex and interdependent MS Excel models, and the impact on analytical quality. By automating a report that previously required numerous file updates and subjective interpretation, the solution demonstrates how structured, dynamic reporting can improve efficiency, accuracy and decision-making support.

4.2.2 Prototype B - Integrated Budget and Real Data Dashboard

Unlike Prototype A, which replicates an existing MS Excel format, Prototype B was developed from scratch to enable the joint analysis of actual and budgetary financial data within a single platform. The model allows for intuitive visual tracking of financial performance and aims to eliminate manual processes traditionally associated with the year-end closing cycle. Additionally, the underlying data tables can be easily exported to MS Excel files, providing structured historical information to support the preparation of budget templates.

This prototype aggregates and visualises financial data from both actual and budget sources, which are traditionally stored in different MS Excel files and consolidated only in higher-level spreadsheets. The MS Power BI version accesses this data directly from its sources, enabling seamless integration and eliminating duplication or file management issues.

The dashboard includes conditional formatting that highlights variances and triggers alerts based on predefined criteria. It also supports dynamic filtering by year or other fiscal dimensions, which eliminates the need to manually restructure MS Excel files at the beginning of each fiscal year. This directly addresses problems associated with the year-end transition process, where old columns must be deleted and new ones added manually.

Furthermore, the dashboard simplifies the initial stage of the budget preparation process. Instead of copying historical data into individual MS Excel files for each department, the MS Power BI interface allows users to filter and view the necessary data with minimal effort. When needed, data tables can still be exported to MS Excel, respecting user preferences and facilitating further analysis or planning in a familiar environment.

Like Prototype A, this model was designed to take advantage of the Copilot feature, which enables natural language interaction with the data and facilitates the generation of insights without requiring technical expertise. However, due to licensing limitations, it was not possible to activate or test this functionality within the scope of the project.

Despite this limitation, the model addresses several key pain points, including data fragmentation, high manual workload and dependence on MS Excel-based processes.

Chapter 5

Demonstration

The demonstration phase plays a crucial role in Design Science Research Methodology, as it involves validating the artifact's ability to address the identified problems and fulfill its intended objectives. Typically conducted through experimentation, simulation, case studies or real-world scenarios, this phase provides empirical evidence of the artifact's effectiveness and reveals any limitations or areas for refinement before broader implementation.

In this project, the demonstration consisted of presenting the developed MS Power BI prototypes to the financial and planning team in a controlled, but realistic setting. The objective was to test the artifact's functionality in relation to the operational challenges identified during the thematic analysis, namely, manual and repetitive work, complex and interdependent MS Excel models, integration of multiple data sources and the impact on analytical quality. This step also laid the foundation for the subsequent evaluation phase, particularly the assessment of Metric 3 – Output Quality.

During the demonstration session, the two prototypes were introduced through structured walkthroughs, using real data and familiar use cases. Stakeholders were encouraged to interact with the dashboards, thereby replicating their regular workflows within a more integrated and automated system. This engagement enabled participants to understand the practical benefits of each prototype, assess usability and reflect on the transition from their current tools to the proposed solution.

5.1 Demonstration of Prototype A - Visual Report Automation Based on Existing MS Excel Templates

Prototype A was developed to replicate a widely used MS Excel-based financial report, structured across multiple interlinked worksheets and manually converted into PDF for stakeholder communication. This format, while visually intuitive, depends heavily on MS Excel file interdependencies and manual updates, both in terms of data input and narrative insight generation.

The MS Power BI prototype was carefully designed to preserve the visual layout of the original MS Excel report, ensuring user familiarity while eliminating the underlying technical limitations. Unlike the MS Excel version, which requires maintaining complex linkages between multiple files, the MS Power BI implementation consolidates all necessary datasets into a centralised and automated data model.

Figure 5.1: MS Power BI Data Model Architecture.

As shown in Figure 5.1, the MS Power BI data model establishes a structured relationship between tables, integrating multiple data sources and eliminating the need for manual data consolidation. This relational model ensures consistency across the report and provides a robust foundation for dynamic analysis.

In addition to structural integration, the prototype includes dynamic insight generation based on DAX measures. These measures were designed to produce automatic textual insights that adapt to the reporting period selected by the user, replicating and enhancing the manually written observations from the MS Excel version.

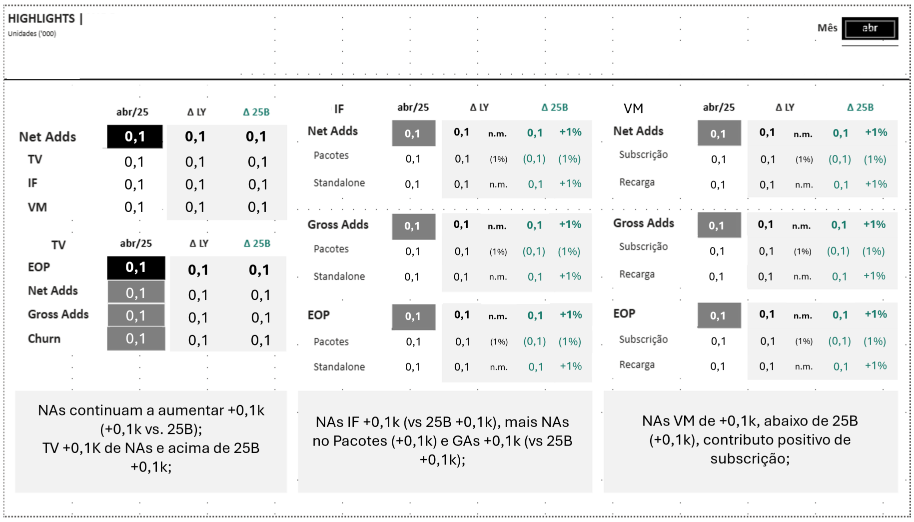

Figure 5.2: Automatically Generated Insights via DAX Measures. Due to privacy concerns, this figure presents an illustrative example based on fictitious data and does not represent actual organisational information.

Figure 5.2 displays an example of these dynamic insights, generated automatically by the system. These insights provide immediate, data-driven commentary based on the selected time period, reducing the cognitive burden on users and enhancing the clarity of analysis.

To complement these functionalities, the report was designed to be visually appealing and intuitive. It presents charts, KPIs and filters in a clean and user-friendly interface that facilitates interaction and supports rapid comprehension.

As illustrated in Figure 5.3, the dashboard layout employs interactive visual elements and consistent formatting to guide user interpretation and engagement. This modern presentation not only mirrors the look and feel of the original report but also significantly increases its usability.

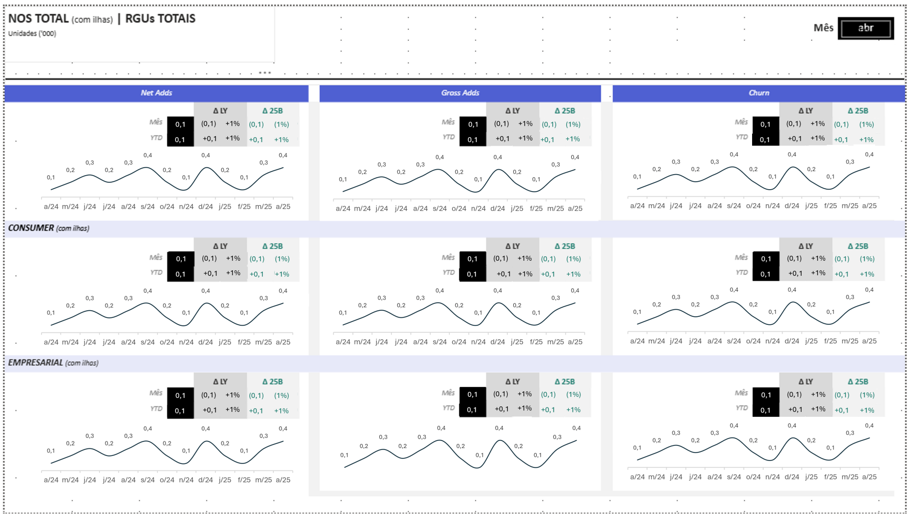

Figure 5.3: Visual Layout of the MS Power BI Dashboard. Due to privacy concerns, this figure presents an illustrative example based on fictitious data and does not represent actual organisational information.

By incorporating these improvements, Prototype A addresses several of the operational challenges identified during the thematic analysis, particularly those related to manual and repetitive work, the complex and interdependent MS Excel models, and the impact on analytical quality. The potential inclusion of Copilot functionality, which was not implemented in this project due licensing limitations, would allow users to explore the dataset through natural language queries, generating new insights with minimal effort and high accessibility.

5.2 Demonstration of Prototype B - Integrated Budget and Real Data Dashboard

Prototype B was developed from the ground up as a new reporting solution, independent of any pre-existing MS Excel layout. Unlike Prototype A, which emulates a static structure, this prototype leverages MS Power BI's native capabilities to deliver a highly interactive, modular and user-friendly interface. Its goal is to consolidate and visualise actual and budget data in a way that enhances analytical depth, enables flexibility and reduces reliance on fragmented MS Excel files.

The dashboard is designed to support continuous financial monitoring, with a structure that promotes ease of navigation and interpretability. One of the key innovations is the implementation of a vertical navigation bar that functions as an index, allowing users to quickly switch between analytical views without the need to return to the dashboard panel interface, which is common in traditional MS Power BI setups.

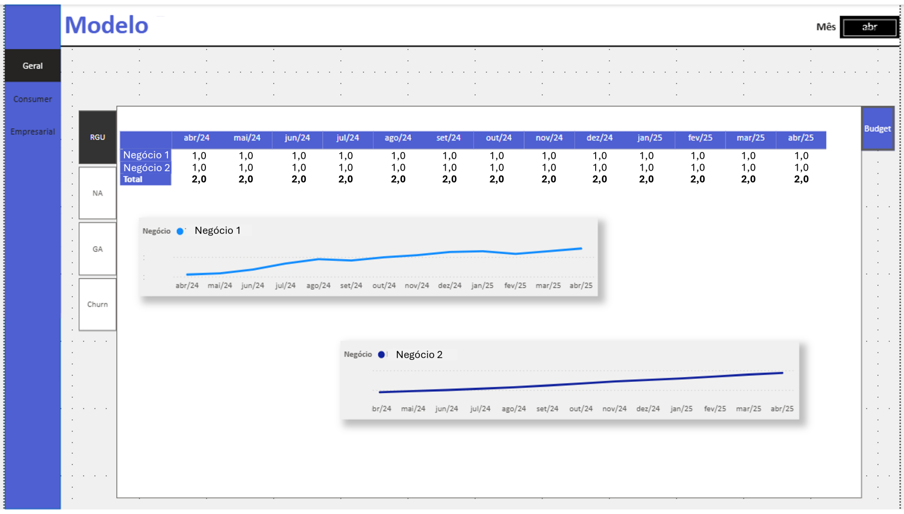

Figure 5.4: Vertical Navigation and Report Layout. Due to privacy concerns, this figure presents an illustrative example based on fictitious data and does not represent actual organisational information.

As shown in Figure 5.4, the dashboard's layout clearly distinguishes itself from static PDF-oriented reports. It is built to be used interactively within MS Power BI, emphasising fluid navigation and the elimination of redundant MS Excel interlinkages.

Within each page, further interaction is enabled through smart controls that adapt the displayed metrics and dimensions. Users can easily change the underlying measure (e.g., churn, gross adds) using internal selectors and filter by specific business areas. The corresponding table and chart are updated accordingly, offering both numerical and graphical representations over a one-year period.

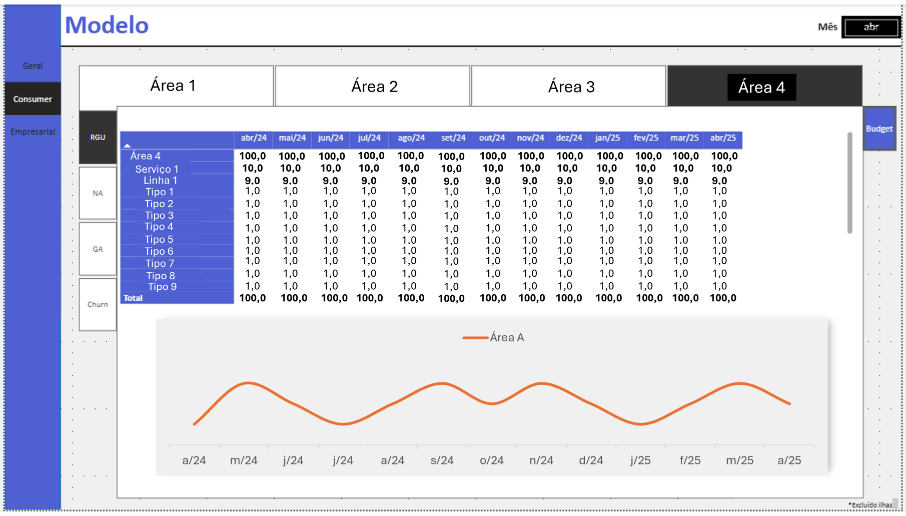

Figure 5.5: Dynamic Metric and Filter Controls. Due to privacy concerns, this figure presents an illustrative example based on fictitious data and does not represent actual organisational information.

Figure 5.5 demonstrates these dynamic components: the vertical menu remains accessible on the left, while the selected dashboard page features embedded tabs that allow for seamless switching between metrics. Filters also enable the narrowing of analysis by area or other relevant dimensions. The chart reflects the evolution of the selected metric throughout the year, complementing the detailed data shown in the table below.

A central analytical component of Prototype B is its side-by-side comparison of actual versus budget data, presented in both graphical and tabular formats. Visual clarity is enhanced through the use of conditional formatting to highlight significant variances. Negative deviations are marked with red circles, while positive deviations are shown with green circles, facilitating immediate interpretation of performance status.

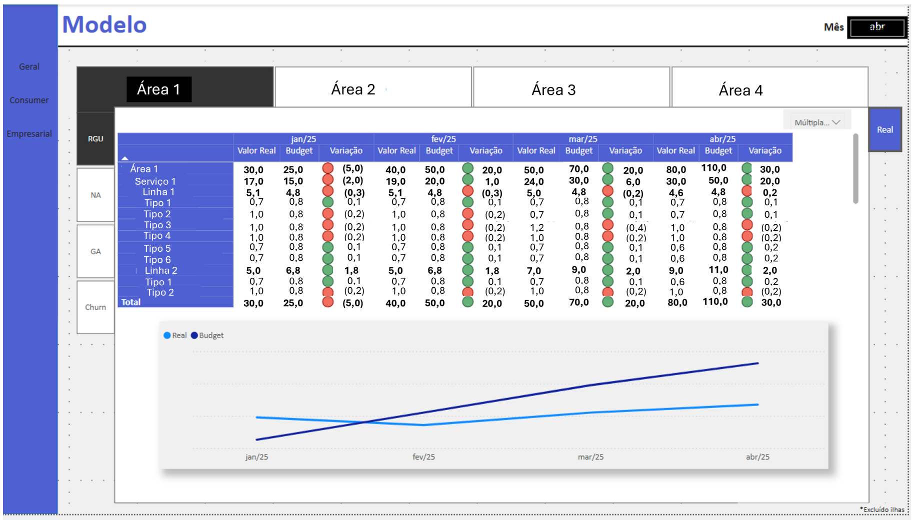

Figure 5.6: Actual vs Budget Analysis with Conditional Formatting. Due to privacy concerns, this figure presents an illustrative example based on fictitious data and does not represent actual organisational information.

As illustrated in Figure 5.6, the chart displays monthly comparisons of actual and budget values, while the accompanying table provides the detailed figures and variance indicators. This layout supports a quick assessment of deviations and trends, reducing the cognitive load on users and improving decision-making quality.

By integrating real and budget data, using visual alerts and intuitive navigation, Prototype B addresses multiple pain points identified in the thematic analysis, particularly those related to the complex and interdependent MS Excel models, the manual effort required for year-end transitions and MS Excel models and files update, and the need for integrated data views. Due to licensing limitations, the Copilot functionality was not tested, however, this functionality enhances user autonomy, enabling natural language queries that generate insights without requiring technical expertise.

Chapter 6

Evaluation

In the context of Design Science Research Methodology, the evaluation phase plays a crucial role in determining the extent to which the developed artifact addresses the problem identified in the initial stages and meets the objectives outlined during the design process. This phase represents a critical transition from the construction of the artifact to its justification, ensuring that the proposed solutions are not only theoretically robust, but also practically applicable within the organisational context.

According to DSR principles, evaluation is integral to assessing the utility, quality and efficacy of the artifact. This is typically achieved through the application of both quantitative and qualitative metrics, chosen based on their alignment with the problem domain and the specific characteristics of the artifact. Evaluation results, in turn, act as a feedback mechanism for refining the artifact iteratively, contributing to its eventual implementation or generalisation.

Building upon the previous phases of this study, the identification of critical tasks, formulation of solution objectives and design of tailored solutions, this chapter presents a structured assessment of each proposed intervention. The goal is to quantify the expected impact of these solutions by comparing the current state of the processes with the projected post-implementation scenario. This evaluation provides essential insights into the artifact's practical relevance and theoretical contribution.

This evaluation phase focuses on five predefined metrics, established during Phase II. These metrics aim to assess the anticipated impact of each solution on the critical tasks previously identified, providing a basis for analysing both feasibility and potential benefit. The framework encompasses multiple dimensions, enabling a comprehensive comparison between the current process state and the projected post-implementation outcomes.

Since the proposed solutions were not implemented, the evaluation relies on a combination of real data, gathered through structured forms, and well-grounded estimates derived from interviews with task owners and subject matter experts. For each applicable metric, an improvement percentage was calculated to quantify the expected gain, facilitating direct comparisons across different tasks and solutions. This dual approach, combining objective data with expert-informed estimations, ensures a rigorous and contextually relevant analysis, in line with DSR's focus on pragmatic relevance and solution effectiveness in organisational settings.

To ensure clarity and transparency, the evaluation results are presented in two formats: (1) summary tables within the chapter, providing concise overviews of each metric by task and solution, and (2) detailed tables in the appendix, offering a complete breakdown of the data and supporting calculations for further reference.

6.1 Metric 1: Time Savings

The time savings metric serves to evaluate the effectiveness of the proposed solutions by measuring the reduction in time spent on each critical task. This metric quantifies the impact of process improvements, reflecting the time savings after implementing the proposed solutions in the Planning and Management Control Department.

As the analysed tasks vary in frequency, some being executed monthly and others annually, two separate formulas were defined:

$$\text{Monthly Time Savings (MTS)} = \text{Monthly Time Before} - \text{Monthly Time After} \tag{6.1}$$

$$\text{Annual Time Savings (ATS)} = \text{Annual Time Before} - \text{Annual Time After} \tag{6.2}$$

Where:

- Monthly Time Before and Annual Time Before represents the amount of time spent monthly/annually on a task before the solution was implemented;
- Monthly Time After and Annual Time After indicates the amount of time spent monthly/annually on the same task after the implementation of the solution;

This approach preserves the natural periodicity of each task type by maintaining separate calculations for monthly and annual tasks. Moreover, the use of the improvement percentage formula allows for a meaningful comparison of efficiency gains across tasks, regardless of their frequency.

The improvement percentage is calculated using the following formula:

$$\text{Improvement (\%)} = \left(\frac{\text{Time Before} - \text{Time After}}{\text{Time Before}} \right) \times 100 \qquad (6.3)$$

This formula calculates the relative improvement in time savings, providing a clear measure of how much more efficient the task execution has become after the solution's implementation.

The data supporting this metric were gathered through a dual-sourcing approach. Firstly, a structured form (Appendix A.2) was used to capture task-specific information such as task type, ownership and estimated time commitments under the current workflow. Secondly, and most critically, a series of interviews were conducted with task owners and subject matter experts. These sessions aimed to simulate the potential impact of the proposed solutions and to estimate the time requirements under an improved scenario. Given that the solutions had not been fully implemented at the time of this study, these estimates were essential for constructing a realistic post-implementation outlook.

Given the complexity involved in MS Excel Model and Files Update, Data Analysis and Insight Generation, Preparation of Budget Templates and Year-End Transition, the operational KPIs reporting was selected as a reference case to evaluate the proposed solutions. This approach enabled the consistent application of the metric across the various tasks, facilitating a coherent assessment of their structural complexity and potential for automation. By focusing on operational reporting as an illustrative example, it was possible to analyse common challenges, test the applicability of the methodology, and derive insights that are transferable to other processes within these tasks.

This expert-informed estimation approach ensured that the projected savings reflected both practical constraints and departmental experience, enhancing the contextual validity of the findings. The data were systematically documented and are presented in Appendix A.5.

Table 6.1 offers a concise overview of the MTS metric for monthly tasks, highlighting each critical task, the proposed solution and the expected percentage improvement. This presentation facilitates a clear interpretation of the efficiency gains achieved through each intervention.

Critical Task	**Proposed Solution**	**Improvement (%)**
Non-AI solutions		
MS Excel Models and Files Update - operational KPIs reporting	MS Power BI automated updates	7%
Data Transfer from ERP to Financial Consolidation System	ERP-Financial Consolidation connector	100%
	RPA to fully automate the extraction	100%
Sending Monthly Reports via Email	RPA for automatic email distribution	100%
Management Information Rules	Native Financial Consolidation System rules	100%
	RPA to automate the process	100%
AI solutions		
Reference Data Classification	Machine Learning Algorithms	40%
Data Analysis and Insight Generation - operational KPIs reporting	MS Power BI for real-time reporting	50%

Table 6.1: Summary of Monthly Time Savings (MTS) Metric.

For tasks with annual frequency, the key results are summarised separately in Table 6.2. This table presents the percentage improvements for each critical task. Separating the data by task frequency ensures clarity and preserves the natural periodicity of the analysed activities.

Critical Task	**Proposed Solution**	**Improvement (%)**
Non-AI solutions		
Preparation of Budget Templates - operational KPIs reporting	MS Power BI dynamic access + export + RPA	80%
Year-End Transition - operational KPIs reporting	Centralised MS Power BI model + integration	80%

Table 6.2: Summary of Annual Time Savings (ATS) Metric.

The time savings metric provides valuable insights into the time efficiency gains achieved through the proposed solutions. It quantifies the reduction in time required to perform critical tasks, allowing for a direct comparison between the pre- and post-implementation states.

By analysing these time savings, the organisation can prioritise areas for further improvement, allocate resources more effectively and ensure that process optimisations are aligned with organisational goals. The MTS metric not only demonstrates the tangible benefits of the proposed solutions but also supports the ongoing refinement of task execution strategies.

The analysis of the results summarised in Tables 6.1 and 6.2 highlights the significant efficiency gains enabled by the proposed solutions. Tasks automated through RPA achieved a 100% time reduction, effectively eliminating human intervention and allowing full automation of previously manual and time-consuming activities. These tasks were traditionally resource-intensive and required considerable time to complete, meaning that the time saved can now be redirected toward more strategic activities such as data analysis, insight generation and decision support.

MS Power BI-based solutions also demonstrated substantial improvements in the operational KPIs reporting process, with time savings exceeding 80% in annual tasks. This translates into a considerable number of hours recovered, enabling staff to focus less on data handling and more on producing value-added analysis and actionable insights.

Although the improvement in the Reference Data Classification task appears comparatively lower in percentage terms (40%). This reinforces the idea that even moderate improvements can have a considerable operational impact, particularly when applied to repetitive and high-volume processes.

Overall, the time savings metric confirms that the proposed solutions contribute not only to greater efficiency but also to a meaningful shift in the role of the Planning and Management Control Department, from manual execution to strategic analysis and performance optimisation.

6.2 Metric 2: Number of Removable Files

The Number of Removable Files metric was designed to evaluate the potential for structural simplification within the existing file management system, which is currently characterised by a high degree of interdependency among MS Excel and MS PowerPoint documents. These dependencies contribute to operational inefficiencies, increase the risk of data inconsistencies and hinder process transparency. The metric aims to estimate how many of these files could feasibly be eliminated or replaced through automation and technological integration.

The number of removable files is calculated using the following formula:

$$\text{Number of Removable Files} = \text{Number of Files Before} - \text{Number of Files After} \tag{6.4}$$

Where:

- Number of Files Before refers to the total number of files currently used in a given process;
- Number of Files After represents the estimated number of files that would remain after implementing the proposed technological solutions;

To express the efficiency gain more clearly, the percentage improvement is calculated as:

$$\text{Improvement (\%)} = \left(\frac{\text{Number of Files Before} - \text{Number of Files After}}{\text{Number of Files Before}} \right) \times 100 \tag{6.5}$$

To support this analysis, a Python-based tool was developed to automatically scan designated directories, extract inter-file dependency information (e.g., formula references, embedded objects), and construct a directed network graph illustrating the file architecture. Clustering algorithms were applied to group related files, highlighting functional groupings and areas of potential simplification.

However, due to organisational constraints, the script was not implemented during the study and the dependency graph was not generated. Specifically, access restrictions to shared team folders, combined with the risk of disrupting existing workflows and information flows, limited the possibility of deploying automated scanning in the live environment. As a result, the identification of removable files was conducted exclusively through sessions with process owners. These discussions relied on the participants' domain expertise and understanding of the operational context to evaluate the necessity of each file. Participants were asked to assess which files could be considered redundant or replicable through automation based on their knowledge of existing workflows. It is important to note that the metric is only applicable to tasks that previously relied on MS Excel-based processes. For tasks involving system-to-system integrations, where no intermediate files were used, the metric is marked as N/A (Not Applicable). This ensures metric relevance and prevents misleading interpretations.

For certain high-complexity tasks, such as MS Excel model and files update, data analysis and insight generation, preparation of budget templates and year-end transition, which are composed of several distinct sub-processes, the evaluation was standardised by focusing on a common reference process, operational KPIs reporting. This selection ensured methodological consistency across metrics and allowed for meaningful comparison of the impact of the proposed solutions.

Critical Task	**Proposed Solution**	**Improvement (%)**
Non-AI solutions		
MS Excel Models and Files Update - operational KPIs reporting	MS Power BI automated updates	45%
Data Transfer from ERP to Financial Consolidation System	ERP-Financial Consolidation connector	N/A
	RPA to fully automate the extraction	N/A
Sending Monthly Reports via Email	RPA for automatic email distribution	N/A
Management Information Rules	Native Financial Consolidation rules	100%
	RPA to automate the process	100%
Preparation of Budget Templates - operational KPIs reporting	MS Power BI dynamic access + export + RPA	36%
Year-End Transition - operational KPIs reporting	Centralised MS Power BI model + integration	45%
AI solutions		
Reference Data Classification	Machine Learning Algorithms	0%
Data Analysis and Insight Generation - operational KPIs reporting	MS Power BI for real-time reporting	50%

Table 6.3: Summary of Number of Removable Files Metric.

To summarise the findings of this evaluation, Table 6.3 presents an overview of the improvement related to the number of removable files used by the department. The table includes each critical task analysed, the corresponding proposed solution and the associated percentage improvement. This high-level summary facilitates a clear understanding of the simplification opportunities identified across processes.

For a more detailed breakdown, a comprehensive table is provided in Appendix A.6. This appendix supports deeper analysis and offers transparency regarding the assumptions and estimations underpinning the metric.

The data analysis indicates that tasks automated through Robotic Process Automation do not result in a reduction in the number of removable files. This is primarily because the original files remain intact, as automation in this context serves to execute routine processes via robotic means, rather than eliminating the files themselves. Therefore, while operational efficiency may be improved through automation, the volume of files is largely preserved.

In contrast, the task related to Management Information Rules demonstrates a complete (100%) elimination of removable files due to the implementation of native Financial Consolidation rules. This integration effectively streamlines the workflow by removing redundant files, thereby reducing manual handling and potential errors. Furthermore, in the context of operational KPIs reporting, solutions utilising MS Power BI achieve only partial file reduction. This limitation arises from the necessity to maintain MS Excel files that serve as primary data sources, as well as the final reports distributed to stakeholders, which may be delivered in either MS Excel or MS Power BI formats. Consequently, only intermediate files generated during the process are eliminated, reflecting a balance between automation benefits and operational requirements.

6.3 Metric 3: Output Quality

The Output Quality metric aims to evaluate whether the proposed technological solutions are capable of delivering outputs that maintain or surpass the levels of reliability, clarity and usability traditionally achieved through manual processes. This metric is essential for validating the effectiveness of automation, ensuring that anticipated gains in efficiency do not compromise the quality of information delivered to end users.

Given the diversity of tasks under analysis, a distinction was made between intelligent automation solutions, namely those based on Machine Learning and Robotic Process Automation, and those supported by tools such as MS Power BI. This distinction reflects the heterogeneity of operational needs identified within the Planning and Management Control Department. While Machine Learning and Robotic Process Automation solutions aim to replicate or enhance human capabilities, either by performing cognitive tasks such as classification and prediction or by automating rule-based and repetitive activities, Microsoft Power BI serves a different purpose. Power BI focuses primarily on improving data accessibility, increasing reporting efficiency and providing advanced visualisation capabilities to support decision-making.

For this metric, ML-based proposals were excluded, as no model was trained, tested or deployed during the study. Consequently, standard performance measures such as accuracy are not applicable in the current evaluation. Similarly, RPA-based solutions were also not assessed under this metric, since none of the proposed automations had been implemented at the time of analysis, making it impossible to objectively evaluate the output quality they would deliver. As such, solutions involving Machine Learning (e.g., Reference Data Classification) and Robotic Process Automation were excluded from this metric as Data Transfer from ERP to Financial Consolidation System, sending monthly reports via email and management information rules).

However, if implementation were to take place, the output quality of ML models could be evaluated using the accuracy metric, defined as:

$$\text{Accuracy (\%)} = \left(\frac{\text{Number of Correct Classifications}}{\text{Total Classifications Performed}} \right) \times 100 \tag{6.6}$$

In contrast, for solutions where output quality cannot be evaluated through objective correctness, such as dashboards or automated reports, a qualitative measure was adopted named the Output Quality Score. This score was obtained through meetings involving key team members responsible for each task. Participants reviewed the prototypes indicated in Demonstration Phase of the proposed automated outputs and collectively agreed on a score from 1 (very poor) to 5 (excellent), reflecting the degree of alignment between the proposed output and user expectations.

The Output Quality Score corresponds to the arithmetic mean of user ratings across six information quality dimensions. These dimensions, derived from the validated framework of Sedera and Gable (2024), ensure conceptual consistency and methodological rigor. The calculation follows:

$$\text{Output Quality Score} = \sum_{i=1}^{6} \text{Dimension Score}_i \tag{6.7}$$

The summary of results is presented in Table 6.4, which consolidates the key findings for this metric. As ML-based solutions and RPA-based solutions were not implemented, only the Output Quality Score is reported. This table provides a comparative view of output reliability across the proposed solutions.

For complex tasks comprising multiple sub-processes, such as MS Excel Model and Files Update, Data Analysis and Insight Generation, Preparation of Budget Templates and Year-End Transition, a consistent evaluation criterion was applied. Specifically, the operational KPIs reporting sub-process was used as a reference across these tasks to ensure methodological alignment and enable a fair comparison of output quality.

Critical Task	**Proposed Solution**	**Output Quality Score**
Non-AI solutions		
MS Excel Models and Files Update - operational KPIs reporting	MS Power BI automated updates	4
Data Transfer from ERP to Financial Consolidation System	ERP-Financial Consolidation connector	N/A
	RPA to fully automate the extraction	N/A
Sending Monthly Reports via Email	RPA for automatic email distribution	N/A
Management Information Rules	Native Financial Consolidation rules	N/A
	RPA to automate the process	N/A
Preparation of Budget Templates - operational KPIs reporting	MS Power BI dynamic access + export + RPA	2
Year-End Transition - operational KPIs reporting	Centralised MS Power BI model + integration	4
AI solutions		
Reference Data Classification	Machine Learning Algorithms	N/A
Data Analysis and Insight Generation - operational KPIs reporting	MS Power BI for real-time reporting	4

Table 6.4: Summary of Output Quality Metric.

A more detailed version of the evaluation, including individual dimension scores and qualitative insights from the participants, can be found in Appendix A.7.

The analysis of the Output Quality metric reveals that, among the proposed solutions, only those involving MS Power BI could be meaningfully evaluated, as they had tangible prototypes available for user assessment. The results indicate a generally positive perception of these solutions, particularly for tasks such as MS Excel Models and Files Update, Data Analysis and Insight Generation, and Year-End Transition, each scoring 4 out of 5. This suggests a strong alignment between the automated outputs and user expectations in terms of reliability, clarity and usability.

However, certain processes, like the Preparation of Budget Templates, received lower scores (e.g., 2 out of 5), highlighting areas where further refinement is needed to meet quality standards. The remaining solutions based on Machine Learning and Robotic Process Automation could not be assessed under this metric, as they had not been implemented at the time of evaluation.

Overall, the Output Quality metric confirms that visual and reporting-based automations can deliver high-quality outputs when well-aligned with user needs, though iterative user feedback and further development will be essential for less mature proposals.

6.4 Metric 4: Cost of Development and Maintenance

The Cost of Development and Maintenance metric aims to provide a comprehensive financial assessment of each proposed technological solution, thereby enabling informed decision-making within the constraints of corporate budgeting. By quantifying the total expected investment, this metric supports the prioritisation of initiatives that optimise value while minimising unnecessary expenditure.

A standardised cost estimation framework was adopted to ensure consistency and comparability across all solutions. This framework breaks down the total cost into three primary components: human resources, software licensing, and infrastructure/technical support. The overall estimated cost is calculated using the formula:

$$\begin{aligned}\text{Cost of Development and Maintenance} = {} & \text{Development Cost} \\ & + \text{Licensing Cost} \\ & + \text{Integration and Infrastructure Cost}\end{aligned} \tag{6.8}$$

The Development Hours component reflects the anticipated effort required for the design, development, testing and deployment phases. These estimates were obtained through structured brainstorming interviews with IT experts and task owners who have direct experience with similar solutions. Their input ensures that the estimates account for solution complexity and customisation requirements. The Average Hourly Rate is based on the organisation's internal standard cost rates, calculated from average salaries and overheads, thereby grounding the labor cost in realistic internal financial metrics.

$$\text{Development Cost} = \text{Development Hours} \times \text{Average Hourly Rate} \tag{6.9}$$

Licensing Cost captures projected expenses for proprietary software tools and platforms necessary to implement the solutions. This includes, for example, licenses for MS Power BI (Pro or Premium), robotic process automation platforms like UiPath or Power Automate, and any specialised software libraries. Licensing fees were gathered from vendor pricing information to reflect accurate current market costs.

The Integration and Infrastructure Cost covers anticipated expenditures associated with connecting new solutions to existing corporate systems, as well as ongoing maintenance, technical support, and infrastructure investments required to sustain the solutions operationally. This component reflects the complexity of integration and the expected involvement of IT teams.

Applying this formula uniformly facilitates a transparent and systematic comparison of the economic impact of each initiative. For further detail on cost breakdowns and assumptions, a more exhaustive table is available in Appendix A.8.

By integrating development and maintenance cost considerations early in the evaluation process, this metric ensures that proposed technological interventions are both financially viable and aligned with organisational priorities, thus promoting a balanced and sustainable approach to technological innovation.

However, while this cost-based assessment provides a useful foundation for comparison, it does not, on its own, determine the overall viability of the proposed solutions. Each initiative entails a significant financial investment and the long-term benefits such as efficiency gains, risk reduction or strategic alignment. Therefore, a more comprehensive evaluation, including a detailed Return on Investment (ROI) analysis, is essential to assess the true value and feasibility of each technological intervention.

6.5 Metric 5: Return on Investment (ROI) Assessment

Following the individual performance evaluation of the proposed solutions, it is essential to assess their economic viability over a medium-term horizon. The Return on Investment (ROI) metric estimates the financial return generated by each solution over a five-year period, providing insights into the extent to which the solutions can generate monetary benefits relative to their total costs of implementation and maintenance.

The ROI is calculated according to the formula:

$$\text{ROI}(\%) = \frac{(\text{Annual Monetary Value of Time Savings} \times N) - (\text{Cost of Development and Maintenance} \times N)}{\text{Cost of Development and Maintenance} \times N} \times 100 \tag{6.10}$$

where:

- Annual Monetary Value of Time Savings is derived by converting the total minutes saved annually (as estimated in Metric 1: Time Savings) into a monetary figure using the formula:

$$\begin{aligned}\text{Annual Monetary Value of Time Savings} = {} & \frac{\text{Monthly Time Savings (min)}}{60} \times 12 \\ & \times \text{Average Hourly Rate}\end{aligned} \tag{6.11}$$

- Cost of Development and Maintenance corresponds to the amount obtained through Metric 4, encompassing development effort, software licensing, infrastructure integration and maintenance expenses;
- N represents the number of years in the analysis (N = 5 in this study);

This metric offers a comprehensive financial perspective, identifying the break-even point where cumulative financial benefits exceed total investment and illustrating the value accumulation trajectory over the solution's lifecycle. The ROI evaluation ensures that economic sustainability complements operational effectiveness, thus guiding informed decisions toward solutions that maximise long-term value.

The summary table 6.5 consolidates each critical task, the associated technological solution and the annual ROI for each of the five years, enabling a structured comparison of projected financial returns. A detailed breakdown of these annual ROI calculations, including assumptions and cost components, is provided in the appendix A.9

Critical Task	Proposed Solution	ROI 1 Year (%)	ROI 2 Years (%)	ROI 3 Years (%)	ROI 4 Years (%)	ROI 5 Years (%)
Non-AI solutions						
MS Excel Models and Files Update - operational KPIs reporting	MS Power BI automated updates	-96,4%	-93,6%	-91,4%	-89,5%	-88,0%
Data Transfer from ERP to Financial Consolidation System	ERP-Financial Consolidation connector	-74,8%	-49,6%	-24,4%	0,8%	26,0%
	RPA to fully automate the extraction	-60,9%	-52,0%	-48,0%	-45,8%	-44,3%
Sending Monthly Reports via Email	RPA for automatic email distribution	-22,4%	-12,2%	-8,1%	-6,0%	-4,6%
Management Information Rules	Native Financial Consolidation rules	-91,9%	-83,7%	-75,6%	-67,5%	-59,4%
	RPA to automate the process	-81,2%	-75,4%	-72,6%	-70,9%	-69,8%
Preparation of Budget Templates - operational KPIs reporting	MS Power BI dynamic access + export + RPA	-90,7%	-86,2%	-83,6%	-81,9%	-80,7%
Year-End Transition - operational KPIs reporting	Centralised MS Power BI model + integration	-76,8%	-58,9%	-44,6%	-33,1%	-23,5%
AI solutions						
Reference Data Classification	Machine Learning Algorithms	23,0%	54,1%	131,1%	208,1%	285,1%
Data Analysis and Insight Generation - operational KPIs reporting	MS Power BI for real-time reporting	-95,1%	-91,4%	-88,4%	-86,0%	-84,0%

Table 6.5: Summary of Return on Investment Metric.

By integrating ROI into the assessment framework, this approach supports a holistic evaluation of the proposed technological solutions, balancing efficiency gains with economic justification to underpin robust and value-driven decision-making.

The ROI analysis presented in Table 6.5 highlights considerable variation in the economic viability of the proposed technological solutions over a five-year horizon. One of the most notable observations is the rapid return generated by the application of Machine Learning techniques, particularly in the task of Reference Data Classification. This high ROI can be attributed primarily to the low development and deployment costs associated with open-source tools and environments such as Visual Studio Code, which do not require recurring licensing fees. In addition, the solution enables a 40% reduction in time spent on monthly tasks, further contributing to operational efficiency and the observed economic benefits.

In contrast, solutions involving deeper system integration, such as the Data Transfer from ERP to the Financial Consolidation System, or the implementation of native management information rules, display highly negative ROI values over the first few years. This reflects the significant development effort involved, including the need for external consultants, system specialists and user training. The implementation require complex system alignment, data mapping and ongoing support.

When evaluating technologies like RPA and MS Power BI in isolation, the data shows consistently negative ROI values over the entire five-year period. At first glance, this may suggest that these solutions are financially unviable. However, this interpretation would be misleading without considering the broader architecture and cost-sharing potential of these tools. For instance, RPA platforms typically require a single licensing fee that enables the deployment of multiple bots across various workflows. Similarly, MS Power BI development efforts often involve building a centralised data architecture that supports multiple reports and dashboards. Thus, although each use case may show individual development costs, the overall infrastructure is shared and scalable. A detailed breakdown of these ROI calculations, including assumptions and cost components, is provided in the appendix A.9.2

Critical Task	**ROI 1 Year** (%)	**ROI 2 Years** (%)	**ROI 3 Years** (%)	**ROI 4 Years** (%)	**ROI 5 Years** (%)
RPA	-30,0%	7,6%	31,0%	47,1%	58,7%
MS Power BI - operational KPIs reporting	-52,0%	-14,9%	14,5%	38,5%	58,3%

Table 6.6: Summary of Return on Investment Metric related to RPA and MS Power BI.

To better reflect this reality, an integrated ROI evaluation of RPA and MS Power BI is presented in Table 6.6. This considers the broader impact and reuse potential of the respective platforms. Under this more holistic view, RPA demonstrates a substantial improvement in ROI between the first and second years. From the second year onwards, the solution yields a positive return, primarily driven by an estimated reduction in manual effort. Specifically, it achieves a 100% reduction in time spent on monthly tasks and an 80% reduction in time required for annual tasks. This efficiency gain enables employees to shift focus towards higher-value analytical tasks.

MS Power BI, on the other hand, shows a positive ROI from the third year onward under the current operational KPIs reporting use case evaluated. This shift is primarily driven by efficiency gains, resulting from the automation and optimisation of reporting and data analysis tasks. Regarding to the operational KPIs reporting, the solution enables a 13% reduction in time spent on monthly tasks and an 80% reduction in time required for annual tasks, substantially improving resource allocation and operational focus. Although the ROI in the initial years remains modest, the trajectory is clearly improving, indicating growing value over time. It is also important to note that the current ROI figures are based on relatively straightforward operational reporting processes. A broader application, such as extending the solution to strategic tasks like P&L reporting models and financial consolidation, could further enhance the return profile over the five-year horizon.

These findings underscore the importance of contextualising ROI figures within a broader architectural and organisational framework. Tools like RPA and MS Power BI may appear inefficient when assessed per use case but can offer substantial returns when deployed as part of an integrated digital strategy.

Chapter 7

Communication

Following the Evaluation phase, where the proposed solutions were critically assessed through estimation and analysis against predefined criteria, this section corresponds to the final stage of the Design Science Research cycle. This stage aims to transparently and systematically disseminate the research outcomes, including the identified problems, the proposed artefacts, the methodologies employed and the results achieved.

This section critically analyses the results obtained from the estimations and theoretical assessment, establishing a clear link between the challenges identified in the Planning and Management Control Department and the proposed solutions. The internship was designed to explore the potential applications of Artificial Intelligence within the Planning and Management Control Department at NOS, with the goal of improving efficiency and generating additional value by freeing up time for deeper analysis and the production of actionable insights. This objective emerged from the observation of several operational limitations in the department, such as a high manual workload, fragmented data sources and the intensive use of MS Excel files for critical tasks. These weaknesses compromised process efficiency and hindered the department's ability to focus on its analytical role, which should increasingly support strategic decision-making.

In this context, the objectives of the proposed solutions centered on four main pillars: (1) reduction of execution time for critical tasks, (2) decrease the number of redundant files, (3) maintain or improve the quality of outputs produced and (4) reduction of solution production and maintenance costs. The analysis of the results, based on estimated metrics, indicates that, overall, these objectives are likely to be met, with relevant variations anticipated between different types of solutions.

During the analysis, it became evident that the majority of identified solutions did not require advanced AI technologies, but rather focused on automation through tools like RPA and MS Power BI. This reflects the department's current need to streamline operational tasks and free up significant amounts of time, enabling staff to redirect their efforts towards more analytical and value-added activities. While AI applications remain promising for enhancing reference data classification and insight generation, the immediate priority lies in addressing structural inefficiencies through process automation and system integration.

Regarding execution time, estimates suggest that the use of Robotic Process Automation could completely eliminate manual intervention in specific routine tasks, resulting in a 100% reduction in time required for monthly tasks and an 80% reduction in time for annual tasks. This impact is particularly significant, considering that these tasks previously consumed several days of work per month. In the case of operational KPIs reporting, solutions developed in MS Power BI are estimated to generate savings of approximately 13% in time spent on monthly tasks and 80% in time required for annual tasks, thereby potentially freeing analytical capacity for higher-value activities. Additionally, the application of Machine Learning techniques contributes to a 40% reduction in time dedicated to monthly tasks, further enhancing operational efficiency.

Concerning the elimination of redundant files, the estimated results vary. The MS Power BI-based solutions are likely to achieve only partial reduction, as they still depend on MS Excel files as the primary data source or final output format. Similarly, Machine Learning solutions maintain the existing number of files, given that their focus is on data processing rather than file restructuring. For RPA solutions, original files would be preserved since the technology emphasises automation rather than altering data sources.

With respect to output quality, user feedback collected on prototypes and preliminary implementations was mostly positive for MS Power BI solutions, particularly for tasks such as MS Excel Models and Files Update, Data Analysis and Insight Generation, and Year-End Transition scored an average of 4 out of 5. However, less mature solutions, such as the Preparation of Budget Templates, received lower ratings (e.g., 2 out of 5), revealing opportunities for improvement. Other solutions, namely those based on Machine Learning and some RPA workflows were not evaluated for output quality, as they had not been implemented at the time of evaluation.

Regarding ROI, significant variation is expected among the proposed cases. Machine Learning applications, such as Reference Data Classification, are projected to demonstrate positive returns within the first year, given the low development cost and use of open-source tools. Conversely, more complex solutions, such as Data Transfer from ERP to the Financial Consolidation System or the implementation of native management information rules, may show negative ROI in the initial years, reflecting consultancy, integration and training costs.

Nonetheless, it is important to note that assessing ROI on a per-solution basis may be misleading. When analysed in an integrated manner, technologies such as RPA and MS Power BI are expected to demonstrate positive ROI from the second and third years, respectively, due to their transversal reuse across multiple processes. This approach enables the dilution of initial costs and maximisation of value created over time.

It is also relevant to highlight that most of the proposed solutions do not rely on advanced AI technologies, but rather on accessible tools with high impact on operational efficiency. Automation of repetitive tasks, centralisation of reporting and system integration are the main value drivers. Nevertheless, these technologies can be enhanced through AI. For example, the development of RPA workflows could be accelerated with generative AI tools, reducing dependence on external consultants. Similarly, natural language-based features and assisted forecasting could be integrated into MS Power BI, extending its analytical potential.

In summary, the results demonstrate that automation and data analysis technologies have a tangible potential impact on transforming the role of Planning and Management Control. By focusing on addressing structural inefficiencies, these solutions create the necessary conditions for the team to transition from operational execution to a more strategic function, centred on insight generation and decision support. The adoption of these technologies, when supported by technical investment, team capacity building and phased implementation, offers a sustainable path to modernising the management control function and similar organisational contexts.

Chapter 8

Conclusion

Artificial Intelligence has been transforming the way organisations manage and analyse information, bringing significant advances in efficiency, automation and support for decision-making. Technologies such as Machine Learning, Robotic Process Automation and Large Language Models allow processing large volumes of data, identifying patterns and optimising processes in innovative ways, increasingly becoming a strategic tool for companies.

However, the literature review revealed some limitations in the study of the application of AI in Planning and Management Control. There are few academic articles that directly address this relationship, as well as a lack of case studies that allow for a practical comparison between different implementations. Furthermore, the available literature lacks detailed information on the specific tools used, requiring more in-depth research in external sources such as websites and reports from specialised companies.

Within this context, the present internship report adopted a Design Science Research methodology, complemented by thematic analysis, to identify critical tasks and underlying challenges within the Planning and Management Control function. Rather than focusing on the evaluation of specific tools, the research sought to understand operational inefficiencies and technological gaps through a structured analytical framework. This process enabled the recommendation of appropriate solutions, both non-AI-based and AI-based, that respond directly to the identified needs.

Notably, the majority of the proposed solutions do not rely on advanced AI technologies, but instead focus on addressing recurring pain points such as manual workloads, repetitive data handling and the integration of fragmented data sources. Tackling these foundational inefficiencies creates the necessary conditions for teams to shift their attention from operational execution to more strategic activities, such as analytical work and insight generation. In this way, automation becomes a catalyst for deeper, value-added contributions within the department.

Proposed solutions were grouped into two categories: non-AI-based and AI-based. This classification ensured a realistic alignment between technology and the operational complexity of each task. While high-complexity activities may benefit from advanced AI such as Machine Learning-based forecasting or natural language interfaces, many of the most impactful improvements stemmed from basic automation, centralisation of reporting and integration of data systems.

Although tools like MS Power BI and RPA are not inherently based on AI, they can be enhanced and supported by AI technologies. For instance, the development of RPA workflows, often hindered by lack of internal expertise, can be significantly accelerated through the use of AI-assisted development tools or generative AI for code suggestions. This reduces dependence on external consultants and lowers implementation costs. Likewise, MS Power BI can incorporate AI-driven insights or natural language query functionalities, thus extending its capabilities beyond basic reporting.

Importantly, these technologies can scale their benefits if integrated across the team. The recommended strategy involves designating a small internal development nucleus of 1–2 existing team members. This does not imply adding new personnel to the department but rather reallocating responsibilities by freeing these individuals from certain routine tasks, thereby partially freeing their time to focus on the design and maintenance of the proposed solutions. However, a key barrier identified is the limited availability of time within teams to initiate such developments. Therefore, a gradual approach is advised, beginning with low-effort, high-impact solutions that free up time, which can later be reinvested in more complex initiatives.

Futhermore, as the present study focused primarily on a representative process — operational KPIs reporting — further work will be required to generalise these findings. A key next step for the internal team will be to systematically evaluate the feasibility of implementing solutions such as MS Power BI across all critical processes within the Planning and Management Control Department. This evaluation should consider process-specific constraints, data availability and integration requirements to determine where automation and reporting enhancements can realistically be applied.

This incremental implementation strategy enables a self-reinforcing cycle of automation and improvement, allowing the organisation to build momentum and internal capabilities over time. AI, in this context, acts not as a stand-alone solution, but as a supporting framework that amplifies the value of well-structured and data-driven processes.

In conclusion, AI and automation technologies offer significant potential to increase productivity, improve decision quality and reduce operational inefficiencies in Planning and Management Control. Their successful deployment, however, depends on a strategic blend of technical investment, capacity-building and phased implementation. By addressing foundational process challenges first and introducing AI where it provides real added value, organisations can create a more intelligent, agile and sustainable management model.

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Appendix A

Appendix

A.1 Semi-Structured Interview Guide

The objective of this interview is to understand the daily tasks carried out with the aim of identifying areas where processes can be improved through the use of technological solutions, including the use of tools integrated with Artificial Intelligence (AI).

1. **Employee Identification**

   1.1. What position do you currently hold?

   1.2. Which team in the Planning and Management Control department do you belong to?

2. **Critical Tasks Description**

   2.1. Do you consider that there are critical tasks or tasks with a greater impact on your work? Which?

3. **Challenges Identification**

   3.1. What challenges do you face in carrying out each task?

   3.2. Are there tasks that you find time-consuming or repetitive? Which?

4. **Identification of opportunities for improvement**

   4.1. Do you think there are tasks that can be improved? Which? How?

5. **Final questions**

    5.1. Would you like to add more information about your work or the department's processes?

A.2 Data Collection Form

Task	Start Time	End Time	Responsible Person	Process

Table A.2.1: Data Collection Form.

A.3 Visualisation of the file dependency network

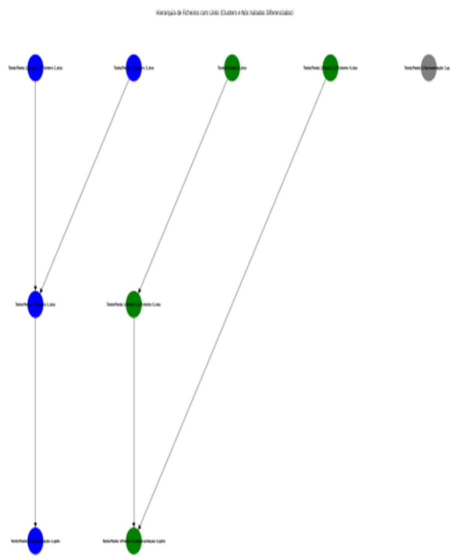

Figure A.3.1: Visualisation of the file dependency network.This figure presents an illustrative example based on fictitious data and does not represent actual organisational information.

A.4 Output Quality Assessment Questionnaire

This questionnaire was designed to evaluate the expected quality of outputs generated by the proposed automated solutions. It is based on the six validated dimensions of Information Quality defined by Sedera and Gable (2024), and it uses a 5-point Likert scale to capture user perceptions.

Instructions:

For each item below, please rate the automated output associated with your task according to your expectations, assuming a successful implementation of the proposed solution. Use the following scale:

- **1 – Very Poor:** The output fails to meet expectations in this dimension and is considered unsuitable for practical use;
- **2 – Poor:** The output demonstrates significant shortcomings that impair its usefulness or clarity;
- **3 – Acceptable:** The output meets minimum expectations but includes notable limitations or areas for improvement;
- **4 – Good:** The output performs well in this dimension, with only minor deviations from optimal quality;
- **5 – Excellent:** The output fully meets or exceeds expectations, offering a high-quality, reliable alternative to manual processes;

Dimension	Description	1	2	3	4	5
Availability	The extent to which the output is expected to be readily accessible when needed.	☐	☐	☐	☐	☐
Usability	The ease with which the output can be used and interpreted by the end-users.	☐	☐	☐	☐	☐
Understandability	The degree to which the output is expected to be clear, logically structured, and easy to comprehend.	☐	☐	☐	☐	☐
Relevance	The degree to which the output contains the necessary information for decision-making.	☐	☐	☐	☐	☐
Format	The appropriateness of the output's visual presentation and layout (e.g., file format, dashboard style).	☐	☐	☐	☐	☐
Conciseness	The extent to which the output provides the required information without unnecessary complexity.	☐	☐	☐	☐	☐

Table A.4.1: Output Quality Questionnaire Based on Information Quality Dimensions.

A.5 Detailed Table of Time Savings Metric

A.5.1 Monthly Time Savings (MTS)

Critical Task	Proposed Solution	Monthly Time Before (min)	Monthly Time After (min)	Monthly Time Savings (min)	Improvement (%)
Non-AI solutions					
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.				7%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.				100%
	Use RPA to automate transfer of data between ERP and Financial Consolidation System				100%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.				100%
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading				100%
	Use RPA to replicate and automate manual adjustment processes.				100%
AI solutions					
Ref Data Classification	Apply Machine Learning for automated reference data classification.				40%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.				50%

Table A.5.1: Detailed Table of Monthly Time Savings (MTS) Metric. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.5.2 Annual Time Savings (ATS) Metric

Critical Task	Proposed Solution	Annual Time Before (min)	Annual Time After (min)	Annual Time Savings (min)	Improvement (%)
Non-AI solutions					
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.				80%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.				80%

Table A.5.2: Detailed Table of Annual Time Savings (ATS) Metric. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.6 Detailed Table of Number of Removable Files Metric

Critical Task	Proposed Solution	Number of Files Before	Number of Files After	Number of Removable Files	Improvement (%)
Non-AI solutions					
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.				45%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.				N/A
	Use RPA to automate transfer of data between ERP and Financial Consolidation System				N/A
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.				N/A
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading				100%
	Use RPA to replicate and automate manual adjustment processes.				100%
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.				36%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.				45%
AI solutions					
Ref Data Classification	Apply Machine Learning for automated reference data classification.				0%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.				50%

Table A.6.1: Detailed Table of Number of Removable Files Metric. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.7 Detailed Table of Output Quality Metric

Critical Task	Proposed Solution	Availability	Usability	Understandability	Relevance	Format	Conciseness	Output Quality Score
Non-AI solutions								
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.	3,0	3,0	4,5	4,0	3,5	3,5	3,6
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Use RPA to automate transfer of data between ERP and Financial Consolidation System	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Use RPA to replicate and automate manual adjustment processes.	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.	2,5	2,0	2,0	3,0	2,5	2,0	2,3
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.	3,5	3,5	3,5	3,5	3,5	3,5	3,5
AI solutions								
Ref Data Classification	Apply Machine Learning for automated reference data classification.	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.	4,0	4,0	4,5	4,5	4,0	3,0	4,0

Table A.7.1: Detailed Table of Output Quality Metric.

A.8 Detailed Table of Cost of Development and Maintenance

Critical Task	Proposed Solution	Development Hours (h)	Average Hourly Rate (EUR)	Development Costs (EUR)	Licensing Costs (EUR)	Integration/ Infrastructure Costs (EUR)	Costs of Development and Maintenance (EUR)
Non-AI solutions							
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.						
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.						
	Use RPA to automate transfer of data between ERP and Financial Consolidation System						
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.						
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading						
	Use RPA to replicate and automate manual adjustment processes.						
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.						
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.						
AI solutions							
Ref Data Classification	Apply Machine Learning for automated reference data classification.						
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.						

Table A.8.1: Detailed Table of Cost of Development and Maintenance. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9 Detailed Table of Return on Investment (ROI)

A.9.1 Independent Solutions

A.9.1.1 1 year

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI (%)
Non-AI solutions						
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.					-96,4%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.					-74,8%
	Use RPA to automate transfer of data between ERP and Financial Consolidation System					-60,9%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.					-22,4%
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading					-91,9%
	Use RPA to replicate and automate manual adjustment processes.					-81,2%
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.					-90,7%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.					-76,8%
AI solutions						
Ref Data Classification	Apply Machine Learning for automated reference data classification.					-23,0%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.					-95,1%

Table A.9.1: Detailed Table of Return on Investment (ROI) - 1 year. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9.1.2 2 years

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI (%)
Non-AI solutions						
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.					-93,6%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.					-49,6%
	Use RPA to automate transfer of data between ERP and Financial Consolidation System					-52,0%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.					-12,2%
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading					-83,7%
	Use RPA to replicate and automate manual adjustment processes.					-75,4%
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.					-86,2%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.					-58,9%
AI solutions						
Ref Data Classification	Apply Machine Learning for automated reference data classification.					54,1%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.					-91,4%

Table A.9.2: Detailed Table of Return on Investment (ROI) - 2 years. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9.1.3 3 years

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI (%)
Non-AI solutions						
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.					-91,4%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.					-24,4%
	Use RPA to automate transfer of data between ERP and Financial Consolidation System					-48,0%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.					-8,1%
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading					-75,6%
	Use RPA to replicate and automate manual adjustment processes.					-72,6%
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.					-83,6%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.					-44,6%
AI solutions						
Ref Data Classification	Apply Machine Learning for automated reference data classification.					131,1%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.					-88,4%

Table A.9.3: Detailed Table of Return on Investment (ROI) - 3 years. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9.1.4 4 years

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI (%)
Non-AI solutions						
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.					-89,5%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.					0,8%
	Use RPA to automate transfer of data between ERP and Financial Consolidation System					-45,8%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.					-6,0%
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading					-67,5%
	Use RPA to replicate and automate manual adjustment processes.					-70,9%
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.					-81,9%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.					-33,1%
AI solutions						
Ref Data Classification	Apply Machine Learning for automated reference data classification.					208,1%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.					-86,0%

Table A.9.4: Detailed Table of Return on Investment (ROI) - 4 years. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9.1.5 5 years

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI (%)
Non-AI solutions						
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.					-88,0%
Data Transfer from ERP to Financial Consolidation System	Implement ERP-to-Financial Consolidation System connector for automated data transfer.					26,0%
	Use RPA to automate transfer of data between ERP and Financial Consolidation System					-44,3%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.					-4,6%
Management Information Rules	Use native Financial Consolidation System rules to automate financial adjustments during data loading					-59,4%
	Use RPA to replicate and automate manual adjustment processes.					-69,8%
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.					-80,7%
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.					-23,5%
AI solutions						
Ref Data Classification	Apply Machine Learning for automated reference data classification.					285,1%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.					-84,0%

Table A.9.5: Detailed Table of Return on Investment (ROI) - 5 years. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9.2 Aggregated Solutions

A.9.2.1 RPA-based Solutions

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI - 1 year(%)	ROI - 2 years(%)	ROI - 3 years(%)	ROI - 4 years(%)	ROI - 5 years(%)
Data Transfer from ERP to Financial Consolidation System	Use RPA to automate transfer of data between ERP and Financial Consolidation System					-30,0%	7,6%	31,0%	47,1%	58,7%
Sending Monthly Reports via Email	Implement RPA to send completed reports to mapped recipients automatically.									
Management Information Rules	Use RPA to replicate and automate manual adjustment processes.									
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel.									

Table A.9.6: Detailed Table of Return on Investment (ROI) – for RPA-based Solutions. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

A.9.2.2 MS Power BI-based Solutions

Critical Task	Proposed Solution	Monthly Time Savings (min)	Average Hourly Rate (EUR)	Annual Monetary Value of Time Savings (EUR)	Cost of Development and Maintenance (EUR)	ROI - 1 year(%)	ROI - 2 years(%)	ROI - 3 years(%)	ROI - 4 years(%)	ROI - 5 years(%)
MS Excel Models and Files Update - operational KPIs reporting	Automate file updates and integrate data sources using MS Power BI.					-52,0%	-14,9%	14,5%	38,5%	58,3%
Data Analysis and Insight Generation - operational KPIs reporting	Implement MS Power BI for data integration, report automation, and error reduction.									
Preparation of Budget Templates - operational KPIs reporting	Use MS Power BI to dynamically access historical data and export it to MS Excel, eliminating the need for manual copy-pasting.									
Year-End Transition - operational KPIs reporting	Create a centralised MS Power BI data model to automate fiscal year transitions, eliminating manual updates in interdependent files.									

Table A.9.7: Detailed Table of Return on Investment (ROI) – for MS Power BI-based Solutions. Blank cells indicate confidential data not disclosed for privacy reasons; only percentage improvements are shown.

Direção de Planeamento e Controlo de Gestão
NOS Corporate Center

Porto, 30th June 2025

Óscar Afonso
Dean of Faculdade de Economia do Porto

Dear Professor,

At this final moment of the project, we would like to give our feedback from the experience with the curricular internship of Marta Alexandra Carvalho Ramalho, within the scope of her master's thesis in Modelling, Data Analysis and Decision Support Systems (MADSAD) at FEP.

The project carried out by Marta Ramalho is part of our strategic journey of digital and analytics transformation of NOS's Planning and Management Control department, and aimed to investigate the potential application of Artificial Intelligence in the role of Planning and Management Control at NOS.

In a nutshell, we would like to highlight the key messages regarding the impact of this project within our team:

- Marta introduced our team, in a very simple and well-structured way, to the main trends in academic literature on AI applications to the typical roles of Management Planning and Control, a subject yet to be more deeply explored within the scope of Data Science & Analytics applied to Management;
- The project provided a very realistic assessment of the main challenges faced by the team, in terms of producing management information and generating insights to support business decisions;
- This assessment resulted from the application of an innovative "Design Science Research" methodology and was based on Marta's hard work involved in interviewing the entire team, processing and systematizing all the data collected, as well as proposing different solutions with a phased implementation roadmap, considering both the technological maturity of the team's activities, and the resources available;
- Marta's work provides insights for future work, which may be addressed by our continued collaboration with FEP's MADSAD Master's program.

The success of this challenging project was only possible because of Marta's determination, resilience, natural curiosity and, foremost, hard work and dedication towards helping to solve our team's needs.

Moreover, I would like to refer that it was very easy to guide and work with Marta, not only because of her enthusiasm to embrace the project, but also because of her "right attitude" that made very natural the way she integrated our team and mobilized us around the research project.

Last but not the least, we would like to express our gratitude towards Professors João Gama and Bruno Veloso, who once again for a fifth consecutive year in this partnership, have allowed us to keep in touch with young talent and state-of-the-art methodologies and academic knowledge, essential to our transformation and innovation journey.

Kind regards,

Cláudia Dias
Head of NOS' TELCO Management Control & Corporate BI