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Big Data Analytics:
An Implementation Framework for the Portuguese Financial Sector

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Big Data Analytics: An Implementation Framework for the Portuguese Financial Sector

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Dedication

To my parents.

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Resumo

Face à crescente necessidade de decisões orientadas por dados, o presente estudo explora como as instituições financeiras em Portugal podem adotar *Big Data Analytics* (BDA) de forma eficaz, através do desenvolvimento de um *framework* estruturado e acionável que responda aos desafios e dinâmicas do setor. Com base na literatura existente sobre BDA, Capacidades Dinâmicas e Modelos de Aceitação Tecnológica, esta investigação procura colmatar a lacuna entre teoria e prática, propondo um modelo integrado adaptado ao contexto financeiro português.

Este relatório propõe um *Adaptive Data Insights Framework* (ADIF) para a implementação de BDA no setor financeiro através de uma abordagem qualitativa baseada em investigação-ação, fundamentada numa combinação de contributos académicos e de um especialista do setor com experiência comprovada. O ADIF visa ultrapassar obstáculos tais como a resistência cultural, baixa literacia digital, infraestruturas desatualizadas e exigências regulatórias. Apresenta uma abordagem estruturada que promove o alinhamento entre estratégias analíticas e objetivos organizacionais, incentivando a adesão dos utilizadores e uma maior adaptabilidade estratégica.

Esta dissertação contribui para a área da gestão ao disponibilizar uma ferramenta prática que os gestores podem utilizar na avaliação e planeamento de iniciativas de BDA. Estabelece uma base para futura investigação empírica, com possíveis aplicações em casos de estudo reais e em contextos organizacionais mais amplos, constituindo um contributo relevante e atual para a academia e para profissionais que procuram reforçar estratégias orientadas por dados no setor financeiro.

Palavras-chave: Big Data; Big Data Analytics; Framework de Gestão; Finanças Portuguesas;

Abstract

In light of the growing need for data-driven decision-making, this study explores how financial institutions in Portugal can effectively adopt Big Data Analytics (BDA) by developing a structured and actionable framework that addresses the specific challenges and dynamics of the sector. Building upon existing literature on BDA, Dynamic Capabilities (DC), and Technology Acceptance Models (TAM), this research aims to bridge the gap between theory and practice via an integrated model tailored to the Portuguese financial context.

Using a qualitative approach grounded in action research, this research proposes an Adaptive Data Insights Framework (ADIF) for the implementation of BDA in the financial sector, based on a combination of academic insights and contributions from an experienced industry expert. The ADIF addresses obstacles such as cultural resistance, lack of digital literacy, outdated infrastructures, and regulatory complexities, offering a structured approach that promotes alignment between analytics initiatives and organizational goals, while also encouraging greater user adoption and strategic adaptability.

This dissertation contributes to the field of management by delivering a practical tool that managers can leverage when evaluating and planning BDA initiatives. It also sets a foundation for future empirical research, with potential applications in real-world case studies and broader organizational contexts. In doing so, it provides both academics and practitioners with a grounded and timely contribution to the advancement of data-driven strategies in the financial sector.

Keywords: Big Data; Big Data Analytics; Management Framework; Portuguese Finance;

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Abbreviation List

ADIF – Adaptive Data Insights Framework

AML – Anti-Money Laundering

BD – Big Data

BDA – Big Data Analytics

DC – Dynamic Capabilities

ERP – Enterprise Resource Planning

GDPR – General Data Protection Regulation

IT – Information Technology

PoC – Proof of Concept

SA – Strategic Alignment

SME – Small and Medium-sized Enterprises

TAM – Technology Acceptance Models

TS – Technology Selection

UA – User Adoption

Chapter 1
Introduction

As data-driven innovation accelerates across industries, the financial sector faces mounting pressure to modernize decision-making processes and optimize operations through advanced analytical tools. In an increasingly complex and regulated environment, the capacity to extract actionable insights from large-scale data has evolved from a competitive edge into a fundamental requirement for institutional sustainability (Gandomi & Haider, 2015; Mcafee & Brynjolfsson, 2012), and yet despite the widespread recognition of BDA as a transformative asset, its adoption within the Portuguese financial sector remains strikingly limited. According to Eurostat (2022), only 10.6% of Portuguese companies have implemented or outsourced data analytics, compared to the EU average of 14.2%. Moreover, 79% of Portuguese firms that collect data reported conducting any form of analysis, suggesting a persistent gap between data availability and its effective use, as stated by the European Commission (2022).

Despite global advances in BDA integration, Portugal continues to face specific obstacles—namely cultural resistance, lack of digital literacy, outdated legacy systems, and limited technological infrastructure—which delay or entirely prevent successful implementation (Mikalef et al., 2019; Sun et al., 2018). In the Portuguese financial sector, these challenges are intensified by strict regulatory constraints, high compliance costs and a historical reliance on traditional decision-making structures (Sivarajah et al., 2017). Nevertheless, the potential of BDA remains undeniable, particularly in areas such as fraud detection, risk modeling, and customer behavior prediction (Davenport et al., 2012; Hashem et al., 2015). The necessity of a structured, actionable framework to support the effective and scalable adoption of BDA within this context is, therefore, both

timely and essential.

Even though previous academic efforts have thoroughly explored the technical and theoretical foundations of BD and BDA, they tend to focus predominantly on broad technological frameworks or on global use cases, often neglecting sector-specific and country-specific contexts (Ferraris et al., 2019; Mohamed & Weber, 2020). There remains a critical research gap in literature concerning implementation strategies tailored to the Portuguese financial ecosystem—particularly those that consider internal resistance, strategic misalignment, or the lack of user engagement as primary barriers (Gupta & George, 2016; Wamba et al., 2017). Furthermore, existing studies generally overlook how DC and TAM can be synergistically integrated into a guiding framework that supports real-world integration (Teece et al., 1997);

In response to this gap, the present research seeks to answer the following question: *"How to develop and implement a structured framework that addresses the key components and barriers in the adoption of BDA in the Portuguese financial sector?"*. The primary objective is to propose a framework that not only addresses technical and strategic dimensions of BDA adoption but also considers organizational dynamics, cultural resistance, and user acceptance. Through this, the study expects to contribute to the development of a comprehensive, actionable roadmap that Portuguese financial institutions can adopt and adapt to accelerate their analytics maturity and long-term competitiveness. By incorporating insights from both DC and TAM, the proposed framework, result of this current dissertation, named ADIF, offers a multidimensional approach that aims to bridge the gap between strategy, technology, and behavior.

This thesis is structured as follows: Chapter 2 presents a review of the existing literature on BD, BDA, and their specific implications within the financial services sector, with a particular emphasis on advantages, barriers, and the Portuguese context. Chapter 3 outlines the methodological approach, which is

based on Action Research and qualitative inquiry, including interviews with an industry expert. Chapter 4 introduces and breaks down the ADIF framework, derived from thematic analysis of empirical findings. Finally, Chapter 5 offers a reflective conclusion that connects the results back to the initial research question, outlines the contributions of the work, and discusses limitations and potential areas for future research.

Chapter 2
Literature Review

In today's hyperconnected digital landscape, the exponential growth of data generated from a wide range of sources—such as social media, Internet of Things devices, financial transactions and artificial intelligence—has significantly transformed the global business environment and led enterprises to reimagine how they operate. The volume, speed, and diversity of what is often referred to as BD has equally created both opportunities and challenges, from both business and technological perspectives (Chen et al., 2012; Davenport et al., 2012).

With the growing volume of complex data, organizations are able to extract valuable insights and make strategic decisions efficiently (Gandomi & Haider, 2015). However, traditional data management methods are currently considered insufficient to handle scale and diversity, requiring the adoption of BDA, to supply advanced tools and to analyze massive datasets in real-time (Sivarajah et al., 2017).

In the financial sector, data from transaction logs and high-frequency trading offers valuable insights but demands analytical capabilities that many firms still lack (Alharthi et al., 2017). Across distinct industries, BD not only fuels operational efficiency but has the ability to ignite breakthroughs in consumer trends, guiding risk assessments and refining strategic decisions.

Therefore, it is essential to explore the concepts of both BD and BDA, evaluate their advantages and challenges, as well as the specific context of their implementation within the Portuguese financial sector.

2.1. BD and BDA

The term BD gained traction around 2011, driven by widespread internet adoption, lower data storage costs, and the digitization of business and consumer activities (Wamba et al., 2017), but the challenges of managing large datasets were already acknowledged as early as 1997 by National Aeronautical and Space Administration (NASA) researchers (Press, 2013). Despite extensive study, a universally accepted definition remains elusive (Gandomi & Haider, 2015), with the most widely recognized definition of BD being provided by Gartner, describing it as "*high-volume, high-velocity, and high-variety information assets that require cost-effective, innovative processing methods to enhance the decision process, insight generation and process automation*" (Gartner, 2023). While BD offers strategic and operational advantages, its complexity presents significant processing and storage challenges

To understand BD, researchers often reference the Five V's Model: Volume, Velocity, Variety, Veracity, and Value (Gandomi & Haider, 2015), with this framework outlining the core dimensions that define BD's complexity and management challenges.

Volume highlights the massive amounts of data generated daily – such as financial transactions, social media, and digital interactions (Mcafee & Brynjolfsson, 2012) – that presents significant challenges for financial institutions in managing large-scale datasets from trading, banking, and compliance activities (Sivarajah et al., 2017), prompting a shift toward scalable, cloud-based solutions (Mikalef et al., 2019).

Velocity addresses the rapid pace of data generation and processing (Tiwari et al., 2018), and in finance, real-time analytics are crucial for fraud detection, high-frequency trading, and dynamic risk management, demanding instantaneous processing and continuous monitoring (Verma et al., 2018).

Variety captures a broad spectrum of data types, including structured and unstructured data, like images and voice (Gandomi & Haider, 2015), requiring flexible analytical methods due to its complexity, such as natural language processing and machine learning (Mikalef et al., 2019), to effectively integrate and analyze data (Sivarajah et al., 2017).

Veracity emphasizes the accuracy and reliability of data, especially vital in financial sectors where data integrity directly influences decisions, compliance reporting, and risk assessment (Upadhyay & Kumar, 2020), while meeting the demand for robust data governance practices and systematic data validation processes (Sun et al., 2018; Sivarajah et al., 2017).

Value reflects the ability to translate raw BD into meaningful insights (El-Kassar & Singh, 2019). In financial services, this involves optimizing risk management, enhancing fraud detection, complying with regulations (Hashem et al., 2015), and by applying predictive analytics and AI-driven models, institutions identify trends, optimize investments, and strengthen decision processes (Mikalef et al., 2019).

BDA is essential for extracting insightful outputs derived from vast datasets, granting organizations the ability to discover hidden patterns and predict future trends (Davenport et al., 2012), with broadly categorized techniques such as Descriptive, Predictive, and Prescriptive Analytics.

Descriptive analytics reviews historical data to identify past trends and anomalies (Assunção et al., 2015), and in finance, its common uses include compliance reporting, investment performance measurement, and client segmentation (Sivarajah et al., 2017).

Predictive analytics leverages statistical models, data mining, and machine learning to forecast outcomes from historical and real-time data (Gandomi & Haider, 2015), with financial institutions applying predictive models with the goal of attaining credit risk evaluation, fraud detection, and customer behavior

prediction (Tiwari et al., 2018).

Prescriptive analytics recommends optimal actions based on predictive insights, using optimization algorithms and AI-supported simulations (Hashem et al., 2015) supporting strategic investment decisions, advanced risk management, and operational efficiency in financial services, and despite these benefits, many smaller institutions still rely on traditional analytics, revealing a notable adoption gap (Sivarajah et al., 2017).

Building on BD's core characteristics (the Five V's) and analytics types (descriptive, predictive, prescriptive), it's clear that successful integration demands more than just technical infrastructure (Chen et al., 2012; Wamba et al., 2017). Financial organizations seeking strategic value from BD must also address organizational and managerial aspects of implementation (Mcafee & Brynjolfsson, 2012), and as such, adopting BD solutions effectively hinges on possessing the right frameworks and capabilities to guide both the technical and human elements of change.

Consequently, the next sections will serve to highlight both current and future benefits and obstacles regarding BDA. Simultaneously, the aim is to also bring to light the direct links to financial companies operating withing the Portuguese scope, and how DC (Teece et al., 1997;Eisenhardt & Martin, 2000) and TAM (Venkatesh et al., 2003) are able to provide the necessary conceptual backbone to ensure sustainable and impactful use of BD within finance in Portugal.

2.2. Advantages and Barriers for BDA Implementation

2.2.1. Advantages

BDA offers substantial benefits that improve organizational performance and strategic processes, and in today's data-driven landscape, companies use BDA to gain deeper insights, boost efficiency, and strengthen competitive positioning (Ferraris et al., 2019). By applying advanced analytics, firms shift from intuition-based to evidence-based strategies, enabling more accurate and effective decisions (Probst et al., 2013). This data-driven approach is especially valuable in finance, where precise risk assessment and predictive insights are critical for profitability and sustainability (Davenport et al., 2012).

A major advantage of BDA is its ability to boost productivity and profitability. By analyzing large datasets, companies can identify inefficiencies, streamline operations, and cut costs (Mcafee & Brynjolfsson, 2012). Advanced analytical tools enable organizations to optimize resource allocation, enhance supply chain efficiency, and improve workforce productivity, leading to increased profitability (Probst et al., 2013). Additionally, BDA enables real-time performance monitoring through key indicators, allowing agile decisions and proactive market responses (Soni et al., 2023).

BDA enhances customer understanding by analyzing behavior, preferences, and feedback, enabling precise audience segmentation and personalized marketing strategies (Russom, 2011); and through the adoption of a customer-centric approach, companies can deliver tailored experiences and increase customer loyalty. Sentiment analysis further captures insights from social media and reviews, revealing consumer expectations (Yaqoob et al., 2016), and also supports predictive modeling to anticipate customer actions and drive proactive campaigns and product recommendations (Brown et al., 2013).

BDA also drives innovation and improves customer experience, and by analyzing market trends, consumer feedback, and emerging technologies, organizations can identify new business opportunities, develop innovative offerings, and optimize customer journeys (Davenport, 2014). In the financial sector, for instance, BDA enables the creation of personalized financial products that boost satisfaction and competitive edge (Soni et al., 2023), with predictive analytics and machine learning further supporting product development and strategic positioning (Kache & Seuring, 2017).

Beyond technological implementation, successful BDA integration requires a cultural transformation within organizations. BDA represents a strategic shift that impacts the entire organizational structure (Upadhyay & Kumar, 2020), and to ensure success, firms must foster a data-driven culture that promotes data literacy, cross-functional collaboration, and data-informed decision-making across all organizational levels (Gupta & George, 2016). This cultural alignment enables both leadership and frontline staff to effectively apply analytics tools in their workflows (Aseeri & Kang, 2023).

The concept of DC, as articulated by Teece, Pisano, and Shuen (1997) and later expanded by Eisenhardt and Martin (2000) and Winter (2003), provides a robust strategic lens for understanding how organizations adapt to volatile environments. DC encompass a firm's capacity to sense opportunities, seize them through appropriate investments and decisions, and reconfigure internal and external assets in response to changing market demands (Teece et al., 1997; Wang & Ahmed, 2007).

In the context of BDA, DC are increasingly recognized as the foundation for leveraging data-driven insights to generate competitive advantage. Studies from Wamba et al. (2017) and Verma et al. (2018) emphasize that the integration of BDA into decision-making and innovation processes is not merely a technological endeavor but a strategic one, deeply rooted in a firm's DC.

Empirical literature supports the notion that firms with embedded BDA operate more effectively across functional units, iterating processes based on real-time data. By transforming analytical outputs into value-generating actions, particularly within finance, agility, compliance, and data precision are paramount. DC enable institutions to align data prowess with strategic reorientation and regulatory adaptation, making them essential to any sustainable BDA implementation framework (Singh & Del Giudice, 2019).

Among the major advantages of BDA are real-time resolutions and cost savings, which become massively amplified when firms align new technologies with DC (Teece et al., 1997), ensuring resources are reconfigured to leverage emerging insights (Eisenhardt & Martin, 2000).

TAM, proposed by Davis (1989), have become central in understanding user behavior toward technological adoption. Built on the psychological foundations of the Theory of Reasoned Action (TRA) (Venkatesh et al., 2003), these models highlight the roles of perceived usefulness, perceived ease of use, and behavioral intention as determinants of technology uptake.

In the context of BDA, particularly within complex and regulated environments like the financial sector in Portugal, user acceptance is a critical success factor (Verma et al., 2018). Recent adaptations of TAM into BDA settings incorporate variables such as system quality, information quality, and business value expectancy (Chang, 2012), emphasizing that adoption depends not only on technical features but also on cultural, organizational, and strategic alignment (SA). As firms scale BDA tools across departments, these models highlight how employee perceptions, digital literacy, and contextual relevance influence integration success (Chen et al., 2012).

TAM complements DC by addressing the human and behavioral aspects of digital transformation, ensuring that strategic change aligns with user engagement, and highlights how perceived usefulness drives employees to adopt

BDA in daily tasks (Davis, 1989). Whenever the working staff witnesses firsthand efficiency and accuracy improvements, from quicker fraud detection to refined customer targeting, they are more likely to adopt advanced analytics systems wholeheartedly (Venkatesh et al., 2003). As a result, combining TAM's user perspective with DC's strategic agility creates a foundation for both operational excellence and innovation.

2.2.2 Barriers

Despite its transformative potential, BDA continues to face significant challenges that limit its broader adoption, particularly in the financial sector, where traditional structures often resist data-driven change. A central barrier is the misalignment between organizational culture and BDA capabilities, as shifting from intuition-led to analytics-based decisions requires a fundamental change in mindset. Many organizations struggle to build a data-driven culture, fostering resistance and skepticism among employees who lack familiarity with using analytics for strategic input (Mikalef et al., 2019) – a situation further complicated by low data literacy, insufficient training, and limited understanding of advanced analytics among non-technical staff (Gupta & George, 2016). As a result, BDA initiatives often remain siloed within departments, limiting their strategic impact and long-term value (Wamba et al., 2017).

Another major challenge is the shortage of professionals with the technical, analytical, and managerial skills necessary to implement and manage BDA solutions effectively (Davenport et al., 2012). The demand for data scientists, machine learning engineers, and AI specialists, far outpaces supply, making it difficult for firms to build capable analytics teams, particularly in countries like Portugal, where data science education is still developing and talent often

migrates toward international opportunities offering higher compensation (Sun et al., 2018). Even when skilled personnel are present, many organizations lack structured training programs that encourage ongoing learning and development, ultimately undermining the long-term success of BDA initiatives (Wamba et al., 2017).

Technological infrastructure limitations remain a significant barrier to BDA implementation, as traditional IT systems often lack the capacity to manage the volume, velocity, and variety inherent to BD, requiring substantial investment in high-performance computing, cloud-based storage, and real-time processing engines (Gandomi & Haider, 2015). This challenge is particularly acute in financial institutions, which depend on robust infrastructures to support real-time applications such as fraud detection, algorithmic trading, and dynamic risk assessment (Verma et al., 2018). Yet, deeply embedded legacy systems complicate the transition to modern analytics platforms, creating both financial and operational burdens (Mikalef et al., 2019). Furthermore, integrating fragmented data sources across departments poses further obstacles, often disrupting the seamless information flow needed for effective BDA (Sivarajah et al., 2017).

Privacy, security, and legal concerns add further complexity to BDA implementation, especially in regulated sectors like finance, where institutions must adhere to frameworks such as GDPR, AML directives, and industry-specific standards (Sun et al., 2018). Ensuring compliance, demands robust encryption, strict access control, and real-time monitoring to protect sensitive data (Gandomi & Haider, 2015), but balancing these safeguards with the accessibility required for analytics often creates friction between compliance teams and data scientists (Wamba et al., 2017). Additionally, Ethical concerns surrounding AI such as algorithmic bias, opacity and accountability introduce legal and reputational risks, reinforcing the need for ethical AI frameworks and proactive regulatory oversight (Hashem et al., 2015).

Financial limitations present a major barrier to BDA adoption, particularly for small and medium-sized enterprises (SMEs), which often lack the resources to invest in advanced infrastructure, cloud platforms, and skilled professionals (Coleman et al., 2016). Implementation costs combined with uncertain returns, deter many SMEs from embracing data-driven strategies (Sun et al., 2018), while the financial risks of non-compliance and data breaches further discourage investment in BDA initiatives (Gandomi & Haider, 2015). In contrast, larger firms with more substantial financial resources are better equipped to absorb these costs and risks, giving them a competitive advantage (Sun et al., 2018).

Despite the potential benefits of BD, many organizations encounter concrete barriers such as low data literacy and rigid corporate structures, which hinder effective integration. TAM views these issues as low perceived ease of use, particularly when employees find analytics tools overly complex (Davis et al., 1989). Similarly, DC theory highlights that without the ability to reconfigure processes or invest in reskilling, firms risk remaining trapped in outdated routines (Teece et al., 1997). In other words, cultural resistance and lack of training not only reduce user acceptance but also impair the agility needed to integrate advanced analytics (Venkatesh et al., 2003), requiring a dual approach for user-centered design improvements (TAM) and structural reconfiguration efforts (DC).

2.3 Portugal and BDA

Research on BDA is rapidly expanding worldwide, with China and the United States leading in this field (Sivarajah et al., 2017). Numerous studies have examined integration across various sectors and regions, including SMEs in the UK (Mohamed & Weber, 2020), Industry 4.0 integration in Hungarian firms

(Horváth & Szabó, 2019), barriers in Bangladeshi manufacturing (Moktadir et al., 2019), the use of BDA in Italian companies (Ferraris et al., 2019;Santoro et al., 2019), and the impact of BDA on organizational performance in Greece (Mikalef et al., 2019b).

In contrast, BDA adoption in Portugal remains limited, with existing research indicating that the country lags behind other European nations particularly in the financial sector (Sun et al., 2018). Eurostat reports that only 10.6% of Portuguese companies have adopted or outsourced BDA, compared to 14.2% across the EU (Eurostat, 2022) revealing a gap that warrants deeper investigation into its root causes. Furthermore, although many Portuguese firms collect data, only 79% conduct any form of analysis, suggesting a disconnection between data acquisition and its strategic use, as per report of the European Commission (2022).

Portugal's business ecosystem is overwhelmingly composed of SMEs, which play a central role in national economic performance. As of 2023, there were approximately 538,175 registered companies in Portugal, of which 536,637 (99%) were SMEs (CEIC, 2023), leaving fewer than 2,000 classified as large enterprises. The dominance of SMEs is particularly evident in sectors such as retail, manufacturing, and professional services, where micro and small businesses form the backbone of employment and value creation. Despite their economic relevance, many Portuguese SMEs struggle to adopt advanced technologies such as BDA due to constraints related to financial capacity, digital skills, and strategic alignment.

The limited adoption of BDA in Portugal stems from a combination of cultural resistance, financial constraints, technological limitations, and regulatory challenges (Santos Pereira et al., 2019). Many firms remain anchored to traditional decision-making methods, resisting the shift toward data-driven strategies (Wamba et al., 2017), a reluctance often reinforced by low data literacy

and a lack of adequate training, which together create a persistent skills gap (Gupta & George, 2016). Financial barriers are particularly pronounced among SMEs, which frequently lack the capital to invest in analytics infrastructure and talent (Coleman et al., 2016), thereby limiting their ability to compete with larger firms that capitalize on data-driven insights for strategic advantage (Sun et al., 2018).

Technological limitations also pose significant challenges for BDA adoption in Portugal, particularly in the financial sector, where traditional IT systems are often inadequate for handling large-scale data processing and advanced analytics (Gandomi & Haider, 2015). Migrating from legacy infrastructure to modern, cloud-based platforms requires substantial investment in real-time processing capabilities and cybersecurity — said costs that many Portuguese firms are unable to sustain (Mikalef et al., 2019a). These challenges persist, like integrating fragmented data sources and managing complex data architectures, especially in institutions that process high volumes of sensitive transactional information (Sivarajah et al., 2017).

Regulatory challenges pose a significant barrier to BDA integration, particularly due to the strict data protection requirements imposed by GDPR. Portuguese firms face high compliance costs and legal complexities in managing data privacy and security, which often deter investment in analytics initiatives (Sun et al., 2018). Additionally, ethical concerns surrounding AI-driven decisions—such as bias and lack of transparency—further intensify the regulatory burden, reinforcing the need for ethical AI frameworks and strong data governance practices (Hashem et al., 2015).

In the Portuguese financial sector, BDA is increasingly adopted for compliance, fraud prevention, and improved client servicing, and DC allow banks to rapidly sense regulatory shifts, such as tighter anti-money laundering provisions, and seize new opportunities for data-driven solutions (Teece, 2014).

Simultaneously, TAM highlight the significance of perceived usefulness among frontline finance employees: if risk analysts view analytics tools as accurate and timesaving, BDA adoption accelerates (Lee et al., 2011). Conversely, without robust internal alignment or top management support — key elements in building DC — BDA systems may remain underutilized (Eisenhardt & Martin, 2000). As such, a holistic approach that includes both DC's strategic agility and TAM's user acceptance perspective is crucial for Portuguese financial institutions seeking sustained value from BD investments (De Mendonca & De Andrade, 2018).

Despite persistent challenges, Portugal's financial sector presents growing opportunities for BDA expansion, driven by increased awareness of its strategic value and the momentum of digital transformation initiatives. Realizing this potential, however, depends on addressing key barriers through targeted investments in technology, workforce training, and regulatory readiness. Moreover, cultivating a data-driven culture and encouraging public-private collaboration can further accelerate BDA integration within the national financial ecosystem.

Despite growing enthusiasm around BDA and its clear strategic advantages, a significant gap persists in the academic literature regarding practical frameworks for successful adoption in the Portuguese business landscape, particularly within the financial sector. Driven by increasing regulatory demands, market volatility, bureaucratic constraints, and intensifying competition, firms are seeking data-driven insights to strengthen their market position. Yet, many remain hesitant to fully embrace BDA, hindered by vague implementation roadmaps, concerns over data governance, uneven data literacy, and the absence of actionable guidance for integrating analytics into existing workflows.

By offering a structured approach that addresses key elements—ranging from technological infrastructure and skill development to data-sharing protocols and

governance—organizations can accelerate their analytics maturity and align BDA initiatives with strategic goals. A shared reference framework also empowers executives, managers, and data scientists to coordinate efforts more effectively, promoting cross-functional collaboration while ensuring compliance with industry regulations. This thesis, therefore, seeks to fill a critical gap by proposing a comprehensive model that Portuguese academics, companies, and financial institutions can adopt, adapt, and apply as a roadmap for unlocking BDA's full potential. In doing so, it responds to a clearly stated need from both scholarly literature and practitioners for an evidence-based tool that not only outlines best practices but also offers actionable guidance for embedding BDA into the daily rhythm of organizational decision-making.

Chapter 3
Methodology

The purpose of the study aims to deepen the understanding of BDA adoption within the Portuguese financial sector, while identifying lingering obstacles, best practices to follow, and the key role of organizational factors in shaping its implementation. Thus, the research question established in order to achieve these goals is as follows:

'**How can a structured framework be developed and implemented to address the key components and barriers in the adoption of BDA in the Portuguese financial sector**?'

Given the complexity of the subject and the need to explore the topic in-depth, this research follows a qualitative approach, drawing from Action Research (AR) principles, by leveraging an iterative process of expert engagement, this study seeks to enhance understanding that supports the creation to a systematic framework approach for BDA adoption.

3.1. Method

This study follows an AR approach within a qualitative research framework, as it integrates practical insights from professionals with theoretical advancements, enabling continuous research adaptation (Shani & Coghlan, 2021). Qualitative research is ideal for exploring complex organizational phenomena, including decision-making processes, human interaction and

institutional behaviors (Denzin & Lincoln, 2007), and given that BDA integration involves multifaceted challenges, a qualitative approach ensures flexibility and responsiveness. Additionally, the iterative and interactive nature of AR supports continuous refinement of the research focus, ensuring alignment between the findings and real-world challenges in the Portuguese financial sector. This alignment is reinforced through ongoing collaboration with professionals, which validates the research as both theoretically sound and practically relevant. This methodology allows for a deeper examination of the innate complexities within organizational structures and processes, making it particularly valuable for analyzing BDA adoption in evolving business environments (Erro-Garcés & Alfaro-Tanco, 2020).

In terms of reasoning, this analysis opts for an inductive research method, meaning knowledge is built through observation and iteration, rather than testing predefined hypotheses. Inductive reasoning is widely used in qualitative research since it allows for theories and conceptual models to emerge from empirical data rather than being predetermined or assumed in advance (Thomas, 2006) The open-ended method helps BDA adoption patterns surface organically, supporting a more nuanced and realistic understanding of industry practices, and by embracing an inductive approach, this research is not constrained by rigid theoretical constructs but instead remains responsive to the evolving realities of BDA integration within financial institutions.

The research in itself is innately exploratory, due to its goal of investigating barriers, enablers, and contextual factors in BDA adoption in the Portuguese financial sector. Exploratory research is especially advantageous for underexplored topics in specific contexts, opening up the discovery of new insights and refined frameworks (A.Stebbins, 2001). Given the dynamic and evolving landscape of BD, an exploratory design guarantees that the study remains open to uncovering unforeseen challenges and strategic opportunities

that influence its adoption. The iterative nature of AR further enhances the exploratory aspect of the study, as new findings continuously shape the direction and refinement of the research.

To secure methodological rigor and comprehensive coverage, the research combines bibliographical research to build a theoretical foundation with fieldwork consisting of semi-structured interviews to capture practical insights from industry experience, grounding findings in both academic and real-world contexts (Bowen, 2009).

3.2. Data Collection

The data collection process is centered on semi-structured interviews, which prove to be one of the most valuable sources of evidence in action research, akin to when utilized in case studies (Yin, 2014). The primary source of data consists of monthly discussion sessions with a senior BDA professional between November of 2024 and February of 2025, each lasting approximately one hour. These sessions focus on identifying key barriers, adoption strategies, and best practices within the financial sector. Following in accordance with the principle of continuous improvement, the central aspect is to build upon each prior session's takeaways and, consequently, lead to incremental modifications, whether by adding, removing or refining components of the framework. Semi-structured interviews allow for insightful questioning while enabling participants to share their experiences in an open and flexible manner (Irvine et al., 2013).

The interview process follows a structured guide to ensure consistency while allowing space for emergent insights. Initially, discussions revolve around the expert's role and the organizational context in which BDA is applied. Subsequent topics include the technological and strategic dimensions of integration, key

resistance factors, and organizational enablers that influence the process. Additionally, the participant is encouraged to highlight advantages, obstacles, and recommendations for improving BDA adoption, and with the aim of facilitating comparability and organization, insights from each session are systematically documented and categorized based on thematic relevance.

3.3. Data Processing

Once the interviews were transcribed, via usage of Microsoft Teams' automatic transcription option and the website TurboScribe, data analysis was conducted using a thematic approach, allowing for a structured interpretation of the qualitative material (Matthew B. Miles & Huberman, 1994). This method was selected to align with the exploratory nature of the study, enabling the identification of recurrent patterns and key insights relevant to the development of the proposed framework. The analysis unfolded in four main stages: familiarization with the data, identification of emerging themes, categorical grouping, and framework synthesis.

After reading through the transcripts in detail, prominent themes began to emerge, such as technological limitations, organizational resistance, strategic misalignment, and cultural factors. These themes were then grouped into broader analytical dimensions that substantiate the construction of the framework's three core pillars.

Finally, findings were categorized across four guiding axes—contextual insights, barriers to adoption, interventions, and expected outcomes, serving as a bridge between empirical evidence and the final structure of the proposed framework. This interpretive process ensured that the framework was both conceptually grounded and empirically validated through the lens of the Portuguese financial sector.

Ethical considerations play a crucial role in research design. All interviews are conducted with the informed consent of the participant, ensuring confidentiality and anonymity, with responses used strictly for research and identifiable details being disclosed. To reinforce this, by maintaining anonymity, it allows for more candid responses, as demonstrated in previous BDA adoption studies (Santoro et al., 2019). Furthermore, the participant has the right to withdraw at any stage without any consequences, and in order to maintain transparency, findings are shared with the interviewee for review and validation before final publication.

Through this methodological approach, the study aims to deepen understanding of BDA integration in Portuguese finance, and by integrating expert knowledge with systematic qualitative analysis, the research aims to provide a structured framework for addressing the key challenges and best practices associated with BDA implementation.

Chapter 4
Results

The increasing complexity and volume of BDA adoption in the Portuguese financial sector have presented significant challenges to organizations striving for effective implementation. As outlined in the previous chapter, the research methodology focused on understanding these challenges by gathering crucial insights from an industry professional with a clear grasp of the necessary know-how, key pain points, and best practices for a successful strategic integration, focusing on minimal losses while simultaneously enhancing overall effectiveness.

A critical gap emerged from this research: organizations often lack a structured, adaptable, and scalable approach to integrating BD technologies while ensuring organizational alignment and user adoption, with existing frameworks tending to focus either exclusively on technological infrastructure or primarily on user engagement, failing to holistically address the interplay between technological, organizational, and strategic dimensions.

To bridge this gap, this chapter introduces the ADIF, a structured approach designed to guide financial institutions through the complexities of BDA implementation.

The results presented in this chapter demonstrate how ADIF provides a systematic yet flexible model for financial organizations to overcome integration barriers, implement best practices, and drive data-driven innovation. Insights from expert interviews and industry data are integrated throughout to illustrate the practical application and impact of ADIF.

4.1. ADIF

The ADIF is proposed as a well-rounded and malleable blueprint aiming to overcome the challenges of BDA adoption within the Portuguese financial sector. Through the research conducted in this study, it became evident that organizations struggle with multiple integration barriers, including technological complexity, user resistance, and strategic misalignment. Existing frameworks and methodologies often fail to comprehensively address these issues in an integrated manner, either focusing too narrowly on technical infrastructure or placing excessive emphasis on organizational culture without considering the interplay between both dimensions.

4.1.1 The Core Principles of ADIF

ADIF is built on three core principles that ensure its effectiveness in guiding financial institutions toward a sustainable and scalable BDA adoption:

DC: Organizations must possess the ability to continuously adapt and reconfigure resources to keep pace with the rapid evolution of BDA technologies. ADIF emphasizes agility in adjusting data strategies, workforce competencies, and infrastructure investments in response to emerging market demands.

TAM: Successful adoption depends on how users perceive and engage with BD tools. The framework leverages technology acceptance theories to enhance usability, training, and onboarding strategies, ensuring that technical solutions align with end-user expectations.

Strategic Alignment (SA): For BDA to be truly impactful, it must integrate seamlessly with an organization's long-term strategic goals. ADIF establishes mechanisms to ensure that data-driven insights translate into business value, rather than isolated technical initiatives.

By balancing technological adaptability, user engagement, and strategic coherence, ADIF ensures that BDA adoption is not just an IT project but a holistic organizational transformation.

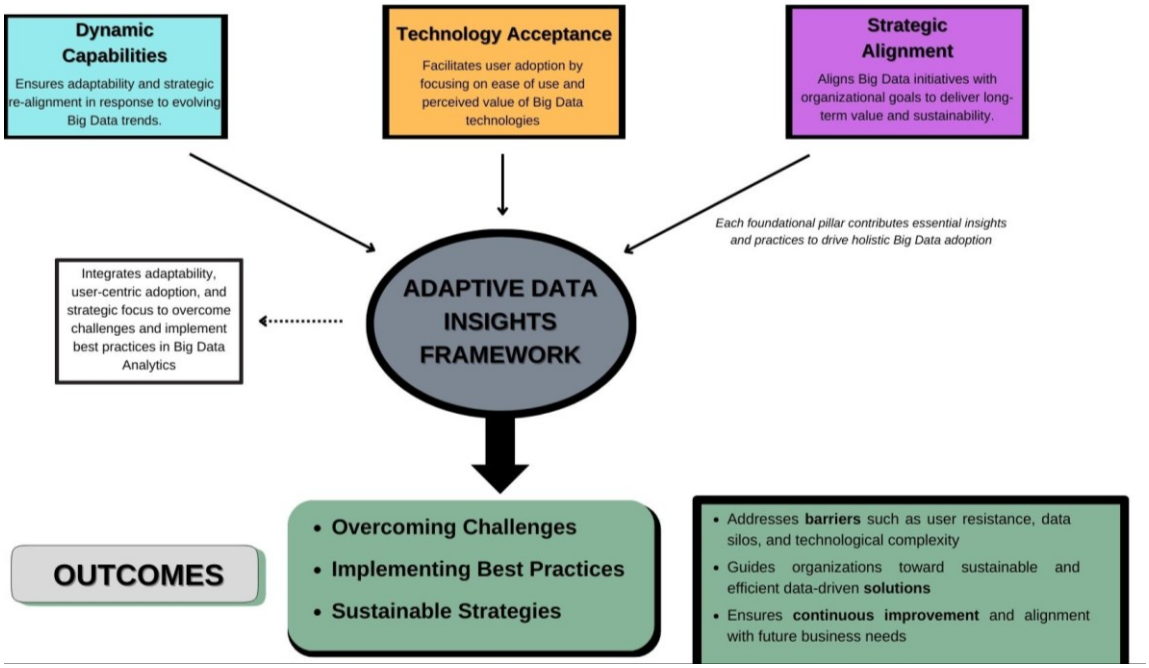


Figure 1 - ADIF and Core Pillars for BDA Adoption.
Source: Author's own elaboration.

4.1.2. ADIF Implementation Process

To effectively bridge the gap between BDA potential and real-world implementation, ADIF follows a phased approach that allows organizations to progressively move from initial adoption challenges to full-scale BD maturity. The framework consists of the following key phases:

Phase 1: User Adoption (UA) – This phase focuses on understanding and addressing organizational resistance, identifying training gaps, and ensuring that stakeholders are prepared and aligned with the adoption of BD solutions.

Phase 2: Technology Selection (TS) – After assessing organizational readiness, this phase guides the selection of appropriate tools and platforms, ensuring that technologies align with business objectives, scalability needs, and compliance standards.

Phase 3: Proof of Concept (PoC) – The final phase ensures that selected technologies and strategies deliver measurable value through real-world testing. Organizations conduct controlled pilots and assessments before scaling full implementation.

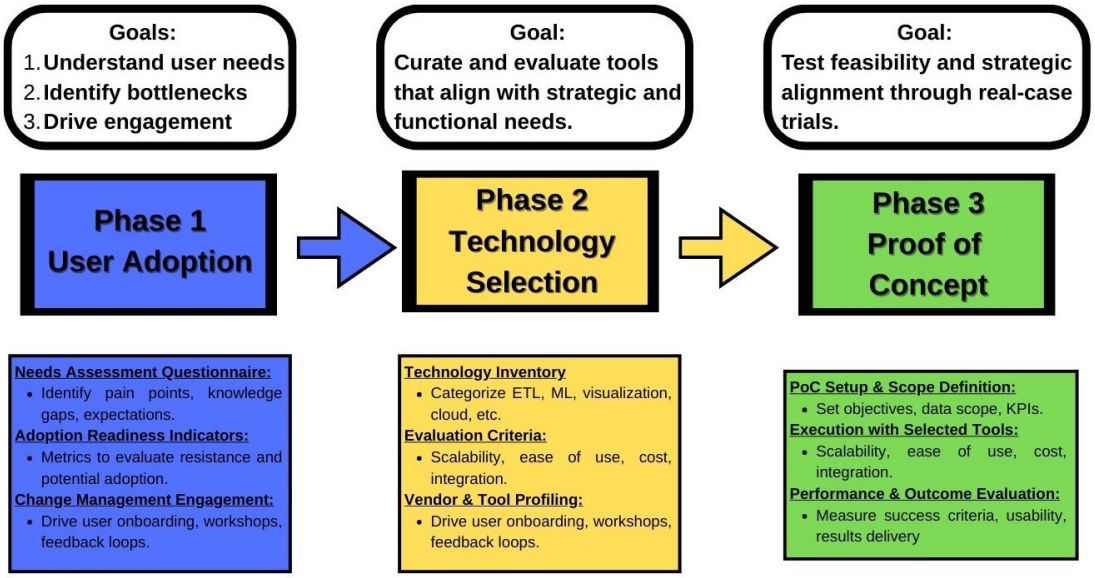


Figure 2 - Three-Phase Implementation Strategy for Successful BDA Adoption in Portuguese Finance.
Source: Author's own elaboration.

Each phase plays a crucial role in ensuring that BDA adoption is sustainable, strategically aligned, and optimized for both technical and business efficiency. The following sections will explore each phase in depth, discussing why each phase is necessary, how it is structured, and the expected outcomes.

4.2. Implementation Phases

4.2.1. Phase 1: User Adoption

One of the most persistent challenges in the adoption of BDA within financial institutions is user resistance. While the technological capabilities of modern platforms continue to evolve, offering unprecedented analytical potential, this progress often clashes with internal reluctance to embrace change. Employees accustomed to traditional tools, such as SQL-based systems or spreadsheet reporting, are frequently hesitant to transition toward more complex, distributed frameworks. As the interviewee highlights, *"Resistance to change is another key challenge…People tend to stick with familiar tools like SQL, even when they're no longer efficient for the data scale"* (See Appendix B).

This reluctance is rarely rooted in a lack of willingness to innovate but more often in a lack of clarity around the practical value of BDA, combined with fears of disruption and a sense of technical inadequacy. This makes the first phase of ADIF not only foundational but critical. Without early and deliberate alignment between people and platform, even the most sophisticated technological implementation risks become underused or misapplied.

The approach within this phase begins with an internal diagnostic: uncovering what exactly is standing in the way of adoption, and by leveraging both interviews and structured survey instruments, organizations can identify specific pain points ranging from insufficient training to poor usability. In many cases, resistance is symptomatic of a broader issue: the lack of an onboarding strategy that caters to different user profiles. As the expert notes, *"The decision-making process must involve not only technology specialists but also business leaders"* (See Appendix B) which is an insight that directly supports the ADIF premise that

integration should be shaped as much by human factors as by technical requirements.

With these frictions identified, the focus shifts to reducing cognitive and emotional barriers to BDA. ADIF promotes a user-centric onboarding methodology, rooted in TAM principles, where perceived usefulness and ease of use drive engagement. This means designing tailored learning paths based on user roles and existing literacy levels—ranging from hands-on workshops for analysts to strategic briefings for leadership. It includes intuitive interfaces and smart platform defaults, minimizing the intimidation factor for non-technical users, as the interviewee emphasizes *"If BD tools are as easy to use as Excel, adoption will skyrocket"* (See Appendix C).

In parallel, the onboarding experience must go beyond theory and focus on concrete application. The expert reinforces this by stating, *"…onboarding programs should focus on practical use cases, not just theoretical training"* (See Appendix C). This supports ADIF's design of onboarding pathways that are role-specific and directly linked to day-to-day workflows. Whether a user works in compliance, finance, or operations, they must immediately recognize how BDA tools simplify and enhance their core responsibilities.

Moreover, adoption is not a one-time event but a dynamic process that must be continuously monitored and refined, which is where metrics come into play. Engagement should be tracked not just in terms of tool usage, but also through qualitative indicators like user confidence, post-training retention, and cross-team collaboration. As the survey instrument outlines, identifying and measuring these factors enables a cycle of feedback and iteration, key in solidifying the cultural shift needed for long-term integration. As the professional adds, *"BD adoption must feel intuitive, with training based on real-world applications"* (See Appendix C), a principle that ADIF directly operationalizes.

When executed well, Phase 1 delivers tangible outcomes: reduced resistance,

higher user engagement, and the establishment of a shared language around data. More importantly, it creates the foundation for the next phase, TS, ensuring that any tools introduced are grounded in the realities of end-user needs and supported by a workforce that is prepared, engaged, and ready to evolve alongside the organization.

4.2.2. Phase 2: Technology Selection

With the workforce aligned and prepared through the UA phase, the next critical step in the implementation of BDA is selecting the right technologies to support long-term integration. The effectiveness of BDA adoption is not determined solely by an organization's willingness to embrace data-driven transformation: it also hinges on the ability to identify, evaluate, and implement tools that align with business needs, scalability requirements, and compliance standards.

Many financial institutions struggle with this process, often overwhelmed by the sheer volume of available BDA solutions, the complexity of integration with legacy systems, and uncertainty regarding long-term sustainability. As the expert explains, *"Traditional SQL databases were not built to handle exponential data growth. That's one of the biggest obstacles companies face when transitioning to BD"* (See Appendix C). This observation reflects a core challenge that ADIF seeks to resolve: bridging the gap between technological potential and organizational reality.

To address these challenges, Phase 2 of ADIF provides an orderly pathway to TS, ensuring that organizations choose solutions that are not only technically robust but also strategically viable. The objective is to move beyond a technology-first mindset and instead prioritize a business-driven selection process, where tools are evaluated based on their ability to deliver operational efficiency,

regulatory compliance, and SA with long-term business goals.

This phase begins with a thorough evaluation of organizational needs and existing technological capabilities. Financial institutions vary widely in their level of BDA maturity—some may already utilize advanced analytics platforms but struggle with scalability, while others may still rely on traditional databases and require an entirely new infrastructure. Through structured assessments, organizations must define their primary objectives for BDA adoption, whether it be real-time analytics for trading operations, predictive modeling for risk assessment, or automation of compliance reporting. This evaluation process is crucial to ensuring that technology investments directly support business objectives rather than serving as standalone IT initiatives.

Once the organization's needs are well-defined, the focus shifts to categorizing and assessing available technologies. BDA tools encompass a wide range of functionalities, from data storage and processing to machine learning and visualization, making it essential to classify solutions based on their role within the data ecosystem. A systematic evaluation matrix allows organizations to compare tools based on key attributes, including scalability, interoperability, security, and cost-effectiveness. Solutions must be analyzed not just in isolation but in relation to the existing infrastructure, ensuring that new technologies integrate seamlessly with core banking systems, ERP platforms, and regulatory compliance frameworks.

The interviewee emphasizes the importance of involving multiple perspectives in this decision-making process: *"If the people responsible for the business area aren't involved in the project from day one, it's very likely the project won't deliver its full value"* (See Appendix C). This is particularly relevant in a sector where regulatory requirements and strategic planning must go hand-in-hand with system architecture. A purely IT-driven selection process may result in tools that meet technical specifications but fail to support actual use cases or strategic

goals.

Another critical aspect of this phase is determining the operational feasibility and long-term sustainability of the selected technologies. Many organizations make the mistake of adopting BDA tools without fully considering factors such as vendor lock-in, total cost of ownership, and required training efforts. ADIF addresses this by guiding institutions through a risk assessment and feasibility study, ensuring that technological investments remain adaptable to future business needs. For example, open-source platforms may offer flexibility but require in-house expertise, while cloud-based solutions may provide scalability but come with data sovereignty concerns.

As the professional puts it, *"Scalability, governance, and adaptability are key enablers of success in modern data ecosystems"* (See Appendix C), which aligns with the DC perspective embedded within ADIF, which ensures that selected tools are not only suited for current needs but can evolve alongside changes in market conditions, customer demands, and regulatory requirements.

By structuring TS as a business-aligned decision process, this phase ensures that financial institutions invest in solutions that deliver long-term value. Furthermore, by applying evaluation matrices (see Appendix F), organizations can approach selection with clarity and accountability—prioritizing performance and integration potential while staying responsive to user-centric considerations established in Phase 1.

The transition from selection to implementation, however, requires practical validation, which is why the next stage of ADIF focuses on PoC and Validation. Before full-scale deployment, organizations must test their selected BDA solutions in controlled environments, assessing their performance, usability, and strategic impact. The following section explores how financial institutions can leverage PoC methodologies to refine their approach, minimize implementation risks, and maximize the value extracted from BDA technologies.

4.2.3. Phase 3: Proof of Concept

Once the right technologies have been selected, the next crucial step is ensuring that they deliver measurable value before full-scale implementation. Many financial institutions face significant hurdles when transitioning from the decision-making stage to operational deployment, often encountering unforeseen issues related to performance, scalability, usability, and integration. Without a structured validation process, organizations risk investing in costly technologies that ultimately fail to meet business expectations or integrate effectively into existing systems.

To mitigate these risks, Phase 3 of ADIF emphasizes the importance of conducting a PoC, a controlled, low-risk environment where selected BDA tools are tested against predefined objectives. The PoC phase is not simply about verifying technical feasibility, but rather evaluating whether the chosen solutions are usable, scalable, compliant, and aligned with strategic needs.

The interviewee highlights the stakes of this phase clearly: *"Companies often underestimate cloud costs—if you don't plan carefully, the operational expenses can quickly spiral out of control"* (See Appendix C). The expert's point underlines why technical testing must be paired with strategic validation — ensuring that resource allocation aligns with long-term value creation, not just short-term functionality.

The PoC process begins by defining clear, organization-specific evaluation criteria. These typically include:

- Scalability – Can the system handle growing data volumes without performance loss?
- Interoperability – Does the solution integrate smoothly with existing

financial systems, databases, and compliance tools?

- Usability – Are end-users able to interact with the system effectively, or do technical barriers still hinder practical adoption?
- Security & Compliance – Does the tool meet regulatory requirements such as GDPR, Basel III, and internal data governance protocols?
- Business Impact – Does the solution enhance strategic planning, drive automation, reduce manual workload, or improve insight generation?

At this stage, insights gathered from Phases 1 and 2 become critical. The user onboarding findings inform how the system is tested by different departments, while the technology evaluation matrices ensure that testing is grounded in measurable outcomes. PoCs that do not consider real user profiles, actual workflows, or compliance demands may produce misleading results—leading to premature rollouts that fail under pressure.

Throughout this phase, cross-functional collaboration is key. The involvement of IT teams, business users, compliance managers, and executive sponsors ensures that the PoC reflects not only technical viability but also strategic fit. Many organizations overlook this type of alignment, resulting in fragmented adoption, resistance, and misconfigured implementations. ADIF addresses this by promoting shared ownership, where stakeholders define success criteria and interpret outcomes.

Moreover, as the professional affirms, *"The architecture has to evolve with the business, not the other way around"* (See Appendix D). This reinforces the importance of flexibility and adaptability, not only in TS but also in the testing approach. A rigid PoC that fails to accommodate feedback or scale with operational demands is unlikely to reflect post-deployment realities.

Once the PoC is completed, findings are analyzed and reviewed to inform the decision on whether to proceed to full implementation. If the results indicate strong performance, usability, and alignment, the solution can be scaled with

confidence. However, if key weaknesses emerge—such as integration failures, adoption bottlenecks, or unexpected compliance risks—adjustments must be made before continuing. In more critical cases, institutions may need to revisit their selection criteria altogether, using PoC insights to inform better-aligned second-round evaluations.

The final output of this phase is not only technical validation but strategic certainty. It confirms whether the chosen BDA tools can sustainably support the institution's operational, regulatory, and analytical needs. When executed according to ADIF, the PoC phase minimizes financial and reputational risk, avoids implementation surprises, and ensures that data-driven transformation moves forward with both agility and confidence.

As a cumulative step, Phase 3 closes the implementation loop by translating strategic intent and technical evaluation into validated business impact. It also sets the stage for continuous improvement—ensuring that BDA capabilities remain aligned with emerging demands in regulation, performance, and decision processes.

Chapter 5
Discussion of Results

A critical reflection between the literature review and the results section unveils a productive synergy between theoretical foundations and more empirical insights. This contrast highlights areas of strong convergence, confirming the solidity and relevance of the ADIF, while simultaneously brings to light distinctive contributions brought forth by the contextualization of BDA implementation in the Portuguese financial sector. This intersection reinforces the robustness of the proposed framework, as many of the research findings align with what has been previously discussed in the literature, while simultaneously addressing existing gaps and overlooked dimensions.

In line with what was mentioned in the literature review, it was possible to verify that BDA plays a transformative role in generating competitive advantage and fostering data-driven innovation, particularly in the financial sector which is inherently data-intensive. Numerous authors recognized BDA's potential to optimize operational processes, enhance strategic decision-making, and improve customer-centric services (Chen et al., 2012; Wamba et al., 2017), with the same findings emerging organically from the empirical phase, as financial professionals consistently emphasized BDA's contribution to agility, market responsiveness, and strategic foresight. This convergence not only validates the academic consensus but also strengthens the credibility of the study's findings, revealing that ADIF is rooted in well-established strategic understandings of BDA's role.

Moreover, the study's insights are aligned with the literature regarding the identification of key challenges associated with BDA adoption. In line with what was identified, it was possible to verify that technological complexity, data

governance issues, organizational resistance, and lack of qualified personnel remain substantial barriers. Authors such as Gupta and George (2016) have extensively discussed these obstacles, and the interviews conducted during this research confirmed their prevalence in the Portuguese context. This overlap further supports ADIF's relevance due to it being grounded in a shared recognition of these structural and organizational bottlenecks, but also evidence that the challenges ADIF seeks to address are not merely anecdotal or context-specific, but rather ones that reflect broader trends acknowledged across the academic domain.

Another point of union lies in the theoretical foundation of the framework, confirming that models such as DC and TAM are essential for understanding the conditions that facilitate successful BDA implementation. Existing studies have long recognized that technical readiness alone is insufficient, and that organizational agility, adaptability, and user acceptance play a decisive role in adoption processes (Teece et al., 1997; (Davis, 1989). The inclusion of DC and TAM within the ADIF framework is consistent with established academic thought, validating the proposition that a given robust implementation strategy must incorporate both strategic and behavioral dimensions in order to achieve pre-established goals. The alignment between theory and practice in this respect confirms the importance of these models, and the results validate their integration into ADIF, making the framework more conceptually sound and operationally relevant.

Additionally, both academic research and observed data emphasize cultural and organizational enablers. According to scientific literature, it was possible to verify that fostering a data-driven culture, enhancing data literacy, and enabling cross-functional collaboration are vital for sustained BDA integration. This aspect, highlighted by scholars like McAfee and Brynjolfsson (2012), was echoed by practitioners, who frequently pointed out the necessity of empowering

employees with a relevant skillset, promoting shared understanding in between teams, and reducing silos between departments, since departmental separation can be detrimental for established goals of efficiency and effectiveness. Once again, this alignment not only strengthens ADIF but also suggests that the organizational side of BDA, often underemphasized in practice, is rightly prioritized in the framework.

The role of regulation and compliance also presents another noteworthy confluence. Particularly in the financial sector, literature already acknowledges the importance of legal and ethical constraints in shaping BDA strategies (Katal et al., 2013; Zarsky, 2017). It was possible to verify that compliance frameworks such as GDPR and AML are seen as both drivers and barriers, with the results confirming this duality: on one hand, regulation demands greater transparency and oversight; on the other, it encourages investment in secure and well-governed analytics systems. The attention to regulatory elements in both domains reflects a mature understanding of the environment in which BDA operates and lends further legitimacy to the regulatory considerations embedded in ADIF.

Another area of alignment is the recognition of BDA as a multi-dimensional phenomenon, with pre-existing research emphasizing that successful implementation requires more than technological deployment; it requires SA, human capital, and organizational readiness (Wamba et al., 2017). The proposed framework confirms this holistic vision by integrating multiple lenses across its phases. It was possible to verify that this multi-layered approach is essential and confirms that addressing BDA through isolated technical upgrades is unlikely to yield sustainable impact, hence requiring careful planning and implementation.

Finally, the need for cross-functional coordination emerges as a shared concern, with literature encouraging internal collaboration between IT squads, data teams, and business units to bridge gaps and ensure shared objectives,

having the results confirm this insight, and advancing further, by structuring this coordination into defined phases (UA, TS and PoC). Feeding from the analysis of existing research, the foundation of such a collaboration is key, with the observed outcomes not only affirm its importance, but also providing practical mechanisms to transform it into an actionable process.

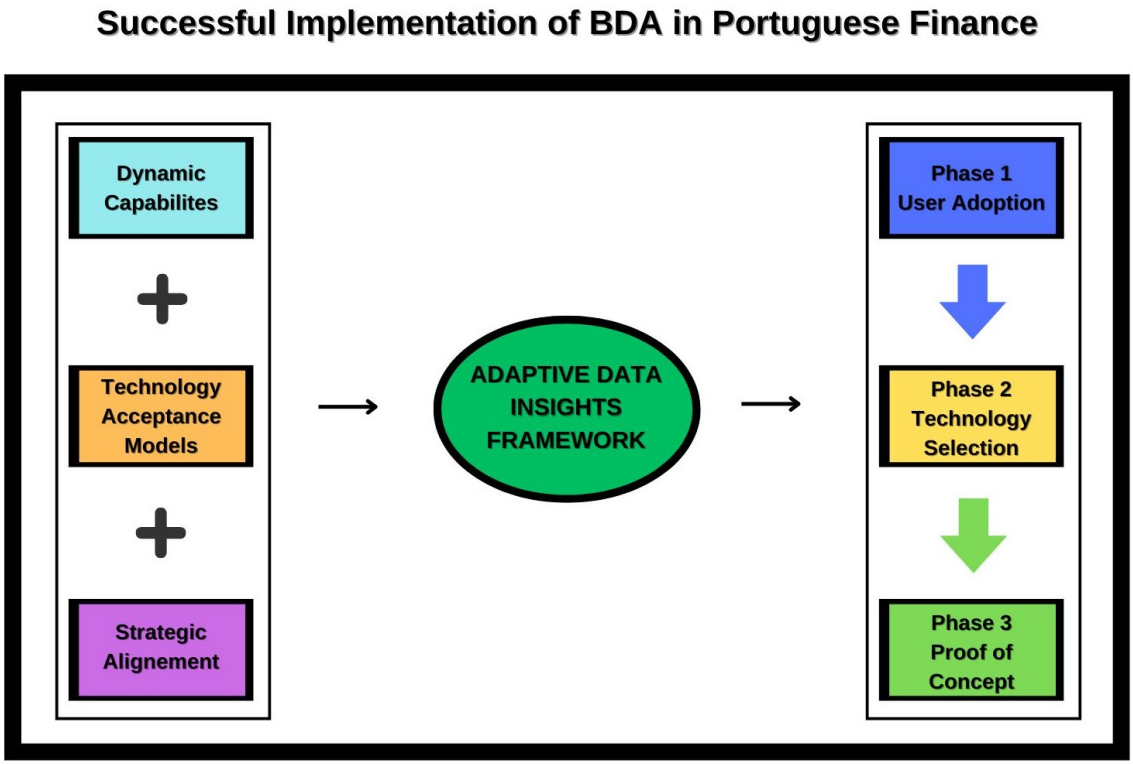


Figure 3 - Integrated Overview of the ADIF and its Implementation Phases for Successful BDA Adoption in Portuguese Finance
Source: Author's own elaboration.

While these similarities validate the research and lend ADIF its theoretical backbone, this study also introduces important distinctions that aim to extend established knowledge, while simultaneously opens up future evolutionary prospects. This aspect wasn't mentioned or referenced or there isn't a lot of focus on it and was taken into consideration for BDA adoption due to the need to tailor strategies to the Portuguese financial sector.

The similarities reinforce the robustness and academic validity of the ADIF

framework, but they also serve a deeper purpose which is to confirm that the extracted findings are not only grounded in established theory, but also aligned with the practical realities of BDA adoption. This alignment lends credibility to the framework as a structured and implementable solution, directly addressing the research question that guided this report. However, the intention of this research was not solely to validate existing knowledge but also to expand on it, and as such, beyond reinforcing what is already known, the results reveal critical gaps and underexplored areas that ADIF actively seeks to address, particularly within the specific context of the Portuguese financial sector. These distinctions mark an important contribution of this thesis and pave the way for future investigation, highlighting where academic discourse and practical needs are yet to fully converge.

Firstly, the assumption of universal applicability prevalent in the literature is challenged, and this stems, in part, from academic works adopting a one-size-fits-all approach, often extrapolating findings across geographies without attending to local idiosyncrasies. This aspect is either left poorly referenced or there isn't a lot of concrete focus on it, without real data backing it up, and was taken into heavy consideration for BDA integration due to cultural resistance, regulatory burdens, and infrastructural disparities unique to Portugal. Grounding the results in local interviews allowed the research to surface nuances that a global view tends to obscure, strengthening the contextual relevance of the framework and making it more actionable for Portuguese organizations.

Second, existing research tends to portray BDA adoption as either a linear or one-time process, which becomes a significant aspect to dissect, relevant due to the increasingly dynamic nature of business environments. In contrast to this, ADIF advocates for a dynamic and iterative perspective, rooted in a structured, evolving and incremental approach, much of which was inspired in DC. It stresses the need for constant reconfiguration of resources and technological

recalibration in response to emerging conditions. This departure is crucial, as it introduces adaptability and flexibility as core principles, an element underdeveloped in much of the existing literature.

A third distinction lies in the overemphasis on technological infrastructure in academic writing. Given that successful implementation hinges as much on human factors, change management, and organizational cohesion as on technical considerations, ADIF's incorporation of TAM and its focus on user engagement and SA remedies this imbalance, offering a more pragmatic and applicable framework. Few studies go beyond technical recommendations, and those that do often miss the combined view that ADIF presents.

Following up, there is a noticeable void regarding actionable implementation roadmaps, and despite many studies offering valuable insights into barriers and enablers, they often lack concrete steps or structures to guide proper execution. Recognizing the need to bridge the gap between strategy and execution, ADIF addresses this gap by introducing a structured, three-phase pathway that is both actionable and adaptable to real-world contexts.

Lastly, internal resistance is often treated superficially in academic discourse, and despite being frequently acknowledged, few studies dig deep into its specific causes or provide targeted mitigation strategies. Acknowledging the high failure rate of BDA initiatives, which are most often driven by user reluctance, fear of automation, and insufficient onboarding, the first phase of ADIF (UA) is purposefully designed to unpack these barriers and provide tailored strategies to overcome them, thereby supporting more effective adoption.

To conclude, the interplay between both the literature and results reinforces the robustness of the ADIF framework, with many of its components being validated by existing academic work, confirming that the framework stands on a solid theoretical backbone, and simultaneously, ADIF innovates by addressing underexplored challenges and offering localized, dynamic, and actionable

pathways for implementation. The research is therefore not only aligned with prior knowledge but also makes meaningful contributions that enhance its practical relevance and academic value, ultimately supporting a well-founded convergence between theory and practice that substantiates the framework's legitimacy and reinforces its applicability within the Portuguese financial sector.

Chapter 6
Conclusion

The dissertation sought to explore how to develop and implement a structured framework that addresses the key components and barriers in the adoption of BDA in the Portuguese financial sector. With this objective in mind, the research aimed to bridge the gap between theoretical constructs and practical challenges, culminating in the creation of the ADIF. Through a combination of literature review and insights gathered from a BD expert, the study attempted to provide a well-founded and context-specific response to the research question.

The findings confirmed that while the potential of BDA is well-recognized within financial organizations, its adoption remains hindered by factors such as cultural resistance, insufficient data literacy, legacy systems, and regulatory complexities. ADIF emerged as a structured approach designed to address these issues by combining the three key pillars of DC, TAM and SA. Each of these elements plays a critical role in ensuring that technological initiatives are not only feasible and scalable, but also embedded in both organizational behavior and long-term goals, with the end result being a framework which aims to promote more efficient onboarding, clearer alignment between data strategies and business needs, as well as greater user engagement with analytics tools.

From a theoretical standpoint, the dissertation contributes to the academic conversation via proposal of an integrated model that links behavioral, strategic, and technological dimensions within the specific context of Portuguese finance, also complementing the literature by offering a framework that can be both adapted and scaled to similar contexts, addressing a noted gap in current academic work. On a practical level, the framework offers decision-makers and practitioners a tangible reference to guide BDA implementation, while taking

into consideration resistance points and internal dynamics that often go overlooked, and by drawing on the perspectives of area experts, and reinforcing findings with empirical insights, the study provides a more nuanced understanding of the challenges and enablers surrounding BDA.

Looking forward, future research should explore the application of ADIF within a real-world organizational setting through a case study approach, having it tested across different institutions and departments, thus allowing its validation and refinement. Expanding the data collection process to include a broader pool of professionals would also enhance the richness of the insights, offering a more comprehensive picture of sector-wide patterns, needs, and obstacles. Additional interviews and possibly even survey instruments could bring in diverse perspectives and increase generalizability with the goal of enriching observable data in a more quantitative way.

Nonetheless, it is important to recognize the limitations of the present study, given the concurrent demands of balancing professional responsibilities and academic obligations, it was not possible to conduct a more extensive field study or expand upon the number of interviewees. Moreover, despite multiple outreach attempts, many ideal, potential participants were unable to collaborate due to scheduling conflicts or overall inaccessibility. As such, the insights presented rely on a single, highly experienced professional, whose contributions proved invaluable for shaping the framework and grounding the research in real operational dynamics.

In conclusion, this dissertation offers a strategic and human-centered lens for understanding BDA adoption in the Portuguese financial sector and while it does not claim to provide a definitive solution, it sets the foundation for future empirical validation and continuous improvement, fostering a clearer pathway for organizations looking to transition toward a data-driven culture.

Appendices

Appendix A – Interview 1 Script

Interview 1 Script

Expert Leader Big Data – *Natixis in Portugal*

11/2024

1. **BDA Introduction** *(5-7 minutes)*

a. Can you tell me a bit about your career path and what led you to become a BA Leader and professional overall ?
b. What does a typical day look like for you in your role?
c. What inspired you to pursue a career in this area, and what keeps you motivated in this field?

2. **Data Management, Technology and Strategy** *(7-10 minutes)*

a. How does your team decide when to use real-time data processing versus batch processing (or database inspired extraction) ?
b. Are there any tools or technologies in BD right now that you think are changing business dynamics as a whole? If so, which and why ?
c. How do you make sure that BD projects align with the overall business goals, strategy-wise ?

3. **Best Practices** *(7-10 minutes)*

a. What are some key practices you've seen that help ensure the data used in BD projects is accurate and reliable ?

b. Could you share a successful BD project you were involved in and what made it work so well ?

4. Overcoming Implementation Barriers *(10-15 minutes)*

a. What common obstacles do companies face when moving from traditional analytics to BD, and how do they get past them ?
b. What strategies have worked well for getting stakeholders on board with BD initiatives ?
c. What do you think are the toughest challenges for companies in the national landscape trying to adopt and make the most out of BDA ? And in the specific banking sector ?
d. Where do you see the field of BDA heading until 2030 ? And beyond that?

5. Adaptive Data Insights Framework (ADIF) *(25-35 minutes)*

a. What are the best practices for implementing a continuously evolving BDA framework within the financial sector, especially in the context of the Portuguese market?
b. What key challenges do organizations in the Portuguese finance sector typically face when trying to scale their data-driven strategies, and how can these be addressed in the framework?
c. How can the framework support overcoming common barriers to data integration, accessibility, and collaboration within financial institutions in Portugal?
d. In your experience, what are the critical success factors for ensuring that best practices in data governance, security, and compliance are effectively implemented in the framework?
e. What strategies would you recommend for engaging stakeholders and overcoming resistance to change when introducing a continuously developed BDA framework in Portuguese financial institutions?

Appendix B – Interview 1 Transcript

Interviewee: Expert (E)

11/2024

1. BDA Introduction

Q1: Can you tell me a bit about your career path and what led you to become a BA Leader and professional overall?

E: I began working in IT when I was 16, during a summer internship at a company that developed imaging software — the kind used in medical environments like MRIs and X-rays. It was a simple experience, but it helped me realize that this was the path I wanted to follow. In high school, I enrolled in a technology-focused informatics course, which required extra effort due to the additional subjects, but it paid off. As soon as I finished, I started a professional internship through the IEFP that placed me directly in a growing field. From there, my academic and professional path always followed a dual track: I worked first and only later formalized my education. I started out as a software developer, first in C and then C#. Over time, I moved through different roles that allowed me to grow in that space until I eventually joined a software development team at the University of Minho. That's where I also decided to pursue a degree in the area, to certify my professional experience. While working there, I got involved with a new Microsoft SharePoint stack that included early Business Intelligence (BI) capabilities — reporting, dashboards, and aggregated views. We started with simple financial reports, expanded into accounting, and then deployed solutions across different schools in the university — engineering, law, sciences, etc. This gave me a new perspective on working with data and was a turning point in my career. That's when I took a postgraduate degree in Business Intelligence at Universidade Portucalense, where I also connected with colleagues who had finished the program. Together, we formed the Associação Portuguesa de Business

Intelligence (APBI). At that time, BI was still unknown in Portugal, and companies lacked the structure and scale to properly invest in data-driven organizations. We started as a small group of friends passionate about the field. Eventually, I joined a Microsoft Gold Partner consultancy, which opened the door to large-scale projects in Portugal and internationally. These experiences helped me specialize in handling large data volumes for BI systems. When you're dealing with organizations at a global scale, the operational data is massive. This naturally led me into the world of Big Data about ten years ago. My first major Big Data project was for Sonae, where we tried to bring Big Data capabilities into the retail space — which wasn't easy. The learning curve was steep, but it sparked my curiosity and made me want to dive deeper into the field. I spent four years working exclusively on Big Data projects, which led to the opportunity at Natixis. The challenge was to migrate a legacy Oracle application into a Big Data ecosystem that leveraged both on-prem servers and cloud environments. It was one of the first Power BI cloud implementations inside Natixis and ultimately led to my current role as Big Data Leader. What makes this area so dynamic — and what keeps me motivated — is that we are constantly adjusting to new realities: the business grows, new acquisitions happen, and we're always being pushed to rethink architectures and bring in new solutions. In recent years, we've also faced geopolitical events like the EU sanctions on Russia, which we had to adapt to in less than 24 hours. That wouldn't have been possible without the Big Data architecture we had in place.

So, my journey has been about continuous learning, staying adaptable, and always looking at how we can bring long-term value from data. I'm driven by the fact that we have a transversal impact on the entire organization. It allows us to understand the full scope of the business and its people, and that human aspect is something that keeps me engaged and motivated every day.

Q2: What does a typical day look like for you in your role?

E: My day-to-day is intense and constantly evolving. We deal with massive data volumes

daily, so ensuring data accuracy, integrity, and value is a constant challenge. It's not just about collecting or ingesting data — it's about ensuring that what we're working with delivers value to the business. We need to continuously adapt our solutions to support growth, regulatory demands, and strategic business decisions. Whether it's ensuring data governance, identifying data owners, or planning for sustainability and scalability, everything requires careful consideration. No two days are the same. We often find ourselves solving immediate problems while also needing to think long-term. The combination of rapid digital transformation and external events — such as market changes or global conflicts — means we need to be constantly rethinking and iterating.

Q3: What inspired you to pursue a career in this area, and what keeps you motivated in this field?

E: What keeps me inspired is the constant evolution of the field. Every week brings new perspectives, especially because we interact with people from all areas of the organization. That gives us a unique, evolving view of the business and its challenges. I'm passionate about building solutions that not only solve today's problems but are also designed to scale and adapt for the future. The opportunity to be in the center of strategic transformation and to contribute to sustainable, data-driven innovation — that's what motivates me every day.

2. Data Management, Technology and Strategy

Q1: How does your team decide when to use real-time data processing versus batch processing (or database-inspired extraction)?

E: There are two core variables that guide our decision: frequency and granularity. Frequency

relates to how often data arrives — whether that's every second, minute, or hour. Granularity, on the other hand, concerns the level of detail the business actually needs. Even if data is available every second, sometimes the business only cares about the daily average. In such cases, it doesn't make sense to overload our systems by processing everything in real time. We'll still collect the data, but we process it later in batch. We have to be conscious of the computing power involved — CPU, memory, storage — and avoid unnecessary system strain if it doesn't bring business value. That's especially critical because the volume of data we manage is huge. There are, of course, situations where we don't get to choose — for example, in trading. Market data changes in milliseconds, and there's no room for delays. Real-time processing is mandatory to keep up with high-frequency trading. Each new data point needs to be processed as it arrives, so we use automated systems with built-in response logic for that. Another concrete example is currency conversion. It happens only once a day but involves processing 300 million transactions. Each transaction has a source and destination currency, and we must calculate conversions for both sides. That's extremely resource-intensive and better suited for batch processing. We also factor in system architecture, volume, and the type of information. Technologies like IoT introduce different constraints — constant sensor data from smartphones or smartwatches changes how we design our pipelines. In summary, while frequency and granularity are the top decision points, the nature of the use case ultimately defines whether we go real-time or batch.

Q2: Are there any tools or technologies in BD right now that you think are changing business dynamics as a whole? If so, which and why?

E: Absolutely. The most significant shift over the last two years has been the integration of artificial intelligence (AI) not just into applications but directly into database technologies themselves. Today, we have AI agents analyzing logs in real time. Instead of manually checking millions of lines for errors, we now use chat interfaces that continuously monitor and interpret logs for us. Similarly, modern query editors come equipped with AI assistants that generate SQL or other query languages from natural language inputs. That lowers the barrier for people without technical backgrounds to explore and interact with data. These advances are transforming how we work with raw data. We're moving toward democratized data access, where even non-technical users can engage directly with data repositories using intuitive tools. That said, none of this works without a solid foundation. Organizations often forget that the true enabler isn't the latest shiny tech — it's the quality and resilience of the underlying data systems. If our databases

aren’t flexible, consistent, and adaptive to change, all the AI tools in the world won’t help. That’s why I always emphasize two pillars: data quality and system adaptability. Our systems must evolve alongside the business. We’re no longer in a world where the database dictates how business processes work — today, it’s the other way around. We also need secure and auditable systems. In banking, if core data goes missing for even an hour, it could mean millions in losses. Business continuity mechanisms — backups, logs, and failover plans — are absolutely non-negotiable.

So yes, AI is changing the game. But it’s the combination of advanced tools and strong data foundations that truly drives transformation.

Q3: How do you make sure that BD projects align with the overall business goals, strategy-wise?

E: Strategic alignment starts with people — specifically stakeholders. If business leaders aren’t involved in the project from the beginning, the initiative is likely to fail or simply never be used. The decision-making process must involve not only technology specialists but also business leaders. No matter how technically impressive the solution is, if the business doesn’t buy into it, there’s no return on investment. That’s why we insist on having stakeholders not just sign off on projects, but actively participate in defining objectives, shaping deliverables, and validating outcomes. We also prioritize forming solid technical teams. A project’s success often comes down to the people behind it — their knowledge, their familiarity with the tools, and their ability to adapt. Sometimes, a well-coordinated team using an older but stable technology will deliver far better results than a flashy project using the latest tools without the right support or know-how. We’re currently witnessing a huge wave of interest in generative AI, and while the potential is real, what worries me is that some organizations are jumping in without ensuring the underlying data is reliable. You can’t build predictive models or intelligent systems on flawed or incomplete data. So, to align BD with business strategy, we balance three things:

1. Strong, committed stakeholders.
2. Teams with both technical and interpersonal competence.
3. A clear understanding that technology is a means to a business end, not the end itself.

When these elements are aligned, we can create projects that don’t just work — they deliver real, measurable value.

3. Best Practices

Q1: What are some key practices you've seen that help ensure the data used in BD projects is accurate and reliable?

E: There are two major dimensions to this: the technological side and the human or business side — and both are equally critical.

On the business side, stakeholder engagement is absolutely vital. If the people responsible for the business area aren't involved in the project from day one, it's very likely the project won't deliver its full value. Even if the technical implementation is solid, if it doesn't align with what the business wants or isn't adopted by the business, it won't generate the return we expect. We need stakeholders who sponsor and support the project throughout — not just by giving approval but by actively participating in design, validation, and ensuring the solution meets their goals. On the human resources side, it's crucial to have the right team. Many organizations get excited by cutting-edge technologies and jump into implementation before considering whether they have the people to support it. That's a mistake. We can't just focus on the tool — we need to invest in talent first. A project is far more likely to succeed when there's a capable and cohesive team behind it, even if the technology isn't the most up to date. In fact, I've seen many successful projects built on stable, well-understood platforms that some might consider outdated — because the team knew how to extract value from them. We're also seeing a strong trend around generative AI and the use of large models. But if the data feeding those models isn't reliable, the output won't be either. That's why data quality must come first — we need trustworthy, well-governed datasets before we even think about automation or AI. So for me, best practices in ensuring data quality come down to:

- Involving stakeholders from the start, aligning with their real-world needs;
- Building teams with the right mix of technical and interpersonal skills;

- Ensuring we have clean, validated, high-integrity data as the foundation;
- And only then applying advanced technologies to generate insight and value.

Q2: Could you share a successful BD project you were involved in and what made it work so well?

E: One example that stands out was a Big Data migration and modernization project we led at Natixis. We were tasked with migrating a legacy Oracle system to a modern Big Data ecosystem that included both on-prem infrastructure and cloud capabilities. It was one of the first Power BI cloud implementations at Natixis, and it was a massive shift. What made the project work wasn't just the technology — it was the way we balanced all the moving parts. We had a motivated and technically skilled team, but we also maintained a constant dialogue with stakeholders. That helped us ensure alignment throughout the project, even when we hit obstacles. And like in any major project, we faced plenty of challenges — moments when things broke down, when we had to pivot or reassess. But we had built up enough trust and clarity around the goals that those inflection points didn't derail us. From a technology perspective, the architecture was designed to support long-term scalability. The data volumes were huge, and we had to think carefully about sustainability, regulatory compliance, and governance. What stood out in this project — and in many others I've worked on — was the strength of the human element: a solid team, committed stakeholders, and a clear understanding of the business value we were aiming for. That's what really made the difference.

4. Overcoming Implementation Barriers

Q1: What common obstacles do companies face when moving from traditional analytics to BD, and how do they get past them?

E: The first and most persistent obstacle is cost. Processing large volumes of data at scale is still expensive, especially for companies that haven't reached a certain level of digital maturity. For businesses that are already data-driven, this is just a line in the budget — a standard operational expense. But for organizations that are not used to making decisions based on data, or don't have digital-first processes, the investment can be intimidating. Even though cloud adoption has helped reduce some infrastructure costs, there are still a lot of companies — especially in Portugal — that are reluctant to use cloud solutions due to concerns about data protection and legal compliance. In my view, this is more of a cultural or mindset issue than a technological one. Our infrastructure in Portugal is excellent. We have fiber optics and data centers that outperform the European average. But the public sector, which should be leading by example, still lags behind. Many public institutions operate with manual, outdated processes, which holds back the country's overall digital maturity. That said, I've seen promising signs — especially with international investment in Portuguese talent and infrastructure. We've proven time and again that we have top-tier academic programs and professional capabilities. If we had more strategic investment, I genuinely believe Portugal could become a European Silicon Valley for data and innovation. So, overcoming these barriers isn't just about money — it's also about shifting mindsets, investing in people, and fostering confidence in modern technologies like cloud and automation.

Q2: What strategies have worked well for getting stakeholders on board with BD initiatives?

E: The number one strategy is involving them from the beginning. They need to feel ownership of the project. It's not enough to present them with a finished product and expect instant buy-in. We show value early on. Whether it's through a proof of concept or by solving a small pain point quickly, demonstrating that Big Data can bring concrete, actionable results helps build credibility. And perhaps more importantly, we focus on trust — making sure the data is accurate, the processes are stable, and the team is reliable.

When stakeholders see that our systems are resilient, compliant, and adaptable to their evolving needs, they feel more confident and are more likely to engage long-term. That trust also comes from communication. We align expectations from day one, we don't oversell, and we're transparent about what's feasible. The more we involve them, the more they become advocates of the transformation.

Q3: What do you think are the toughest challenges for companies in the national landscape trying to adopt and make the most out of BDA? And in the specific banking sector?

E: Nationally, again, the biggest issue is mindset and maturity. Resistance to change is another key challenge. While we have great infrastructure and talent, many organizations still hesitate to fully embrace data-centric strategies. In the banking sector, the challenges are even more specific. Compliance and regulatory requirements are extremely strict. Things like data protection, cybersecurity, auditability — these aren't just good practices; they're non-negotiable. That means we often can't rely on off-the-shelf cloud solutions, and we have to engineer complex architectures that meet both business needs and legal constraints. Another big challenge is legacy systems. Many banks still rely on very old platforms — I'm talking about green-screen terminal systems, stuff from decades ago. Those systems are deeply embedded in daily operations and can't be ripped out overnight. That creates bottlenecks in data integration and automation. We also deal with strict data exchange protocols, like SWIFT messages, which haven't evolved much over the years. That limits how flexible we can be in modernizing our pipelines. And despite progress, there's still a lot of manual work and bureaucracy in banking processes, which slows down transformation. The good news is that many of those processes are already being automated — especially in backoffice operations — and technologies like Power Platform and AI-driven automation are making it easier for non-technical staff to build their own solutions. We call this the "citizen developer" model. It's democratizing access to innovation within the organization, which helps us evolve even under tight constraints.

Q4: Where do you see the field of BDA heading until 2030? And beyond that?

E: I think we're only seeing the beginning of what BDA can do — especially when it comes to how it integrates with AI. The mass adoption of AI tools is pushing organizations to rethink how they handle data end-to-end. In companies that are digitally mature, these tools will be game changers. They'll automate repetitive tasks, enhance decision-making, and speed up insights. But in less mature companies, without clean and reliable data, the benefits won't materialize. You can't automate what you don't understand or control. That's why I believe the future lies in combining AI with a strong foundation in data governance, flexibility, and system resilience. We're also seeing a major shift in user interaction — today, you can write a query in plain language and AI will translate it into a database command. That changes everything. It's not just for data scientists anymore. Everyone can have access to insights. So, by 2030, I expect organizations will be far more fluid, data will be much more accessible, and people in every role — not just IT — will be empowered to work with data directly. But again, the key is getting the foundations right: governance, quality, and long-term thinking.

5. Adaptive Data Insights Framework (ADIF)

Q1: What are the best practices for implementing a continuously evolving BDA framework within the financial sector, especially in the context of the Portuguese market?

E: First, it's critical to recognize that frameworks like this are not static. They need to be flexible enough to evolve alongside both the business and the market. In Portugal, the financial sector has made progress in terms of infrastructure and talent, but regulatory and organizational inertia can still slow things down. To implement something that's continuously evolving, you need to embed adaptability at every level — technical, organizational, and human. That starts with building modular architectures: systems that

can scale horizontally, that are cloud-ready, and that allow for fast integration of new tools and data sources. Then you need governance. Good data governance isn't just about compliance — it's about knowing who owns what, who validates what, and making sure the data adds value. And of course, stakeholder involvement is essential. If your business units aren't engaged, the framework will be seen as a tech initiative instead of a strategic enabler. So best practices include modularity, strong governance, automation where possible, and ongoing stakeholder alignment — all while maintaining compliance and security front and center.

Q2: What key challenges do organizations in the Portuguese finance sector typically face when trying to scale their data-driven strategies, and how can these be addressed in the framework?

E: The main challenge is legacy — both in systems and in mindsets. A lot of financial institutions are still running on outdated architectures that weren't built for scale. Scaling in this context doesn't just mean adding more data; it means being able to process it, use it, and extract value from it — all without breaking what's already in place. That's hard to do when you're dealing with green-screen terminals or batch-based data pipelines. The framework needs to account for this by including transitional strategies: hybrid architectures, phased migrations, and tools that bridge legacy systems with modern platforms. Then there's the organizational side. People aren't always ready for change. Training, change management, and clear communication must be part of the framework — it can't just be about tech. And finally, there's the issue of budget and investment risk. Many companies are afraid of investing in something they're not sure will return value. That's why proofs of concept (PoCs) are crucial. You need to show quick wins, then scale them out. The framework should guide this process explicitly.

Q3: How can the framework support overcoming common barriers to data integration, accessibility, and collaboration within financial institutions in Portugal?

E: First, the framework has to embrace the complexity instead of fighting it. You're going to have fragmented systems. You're going to have silos. So the solution is to build bridges — through APIs, ETL layers, and event-driven architectures that let systems talk to each other without needing full rebuilds. Accessibility doesn't just mean technical access — it also means making data usable by non-technical people. So, data catalogs, self-service platforms, and semantic layers should be built into the framework to empower wider adoption. Collaboration is a cultural challenge. You need governance models that encourage cross-team alignment. That means defining shared KPIs, data definitions, and accountability structures. And yes, sometimes it means breaking a few comfort zones. But without that alignment, collaboration dies. So the framework must be proactive in providing not only the tools and connections, but also the guidelines, roles, and governance to ensure integration and collaboration are the norm — not the exception.

Q4: In your experience, what are the critical success factors for ensuring that best practices in data governance, security, and compliance are effectively implemented in the framework?

E: Number one: resilience. Your system must be able to recover from failure — whether that's technical, regulatory, or human error. Business continuity is non-negotiable. Number two: clarity of ownership. Every piece of data should have someone responsible for its quality, access, and lifecycle. That's what makes governance real — not just policy slides. Then we have security — especially in banking. You simply cannot afford to mishandle data. That means not only encryption and access controls, but also auditability. You need to be able to say who touched what, when, and why. Compliance is more than a checklist — it's a living part of the architecture. Whether it's GDPR, PSD2, or internal risk rules, the framework must adapt to new requirements without breaking down. That means version control, robust change management, and constant testing. So the success factors are clear accountability, resilience, adaptability, and embedding compliance into

the very fabric of the framework — not as an afterthought, but as a driver of trust and sustainability.

Q5: What strategies would you recommend for engaging stakeholders and overcoming resistance to change when introducing a continuously developed BDA framework in Portuguese financial institutions?

E: Bring them in early. Make them part of the design, not just the approval process. If stakeholders see themselves in the solution, they'll support it. Communicate constantly. Transparency builds trust. Share the vision, show the roadmap, and give them ownership of outcomes. Also, tailor the message — executives care about risk and ROI; business users care about time saved and simplicity. Speak their language. Another key strategy is quick wins. Deliver something small but impactful early in the process. That builds momentum and demonstrates credibility. And finally, education. Help people understand the "why" behind the change. Not just how to use the tools, but why the framework matters, why it's a strategic move, and how it'll make their lives better. Change is hard — especially in highly regulated, risk-averse environments like banking. But with the right strategies, you can turn resistance into engagement, and engagement into ownership.

Appendix C – Interview 2 Transcript

02/25

Interviewee: Expert

Q1. What kind of research or information should be gathered before implementing a BDA framework like ADIF in a resistant organization?

E: A critical first step before any attempt to implement a BDA framework is performing a thorough diagnostic of the current environment — both technically and culturally. You need to identify two major dimensions: *pain points* and *bottlenecks*. Pain points refer to the challenges users face with existing tools — for instance, whether certain processes are taking too long, whether there's data fragmentation, or if tools lack user-friendliness. Bottlenecks, on the other hand, can emerge even when the tools themselves are effective; they might exist in processes, coordination, or data flows that delay insights. This distinction is important because it changes the type of response you offer in the framework. If BD tools are as easy to use as Excel, adoption will skyrocket. For example, a team might already have robust SQL skills and tools, but if they're struggling with rapidly increasing data volumes — say, adding 30 million records per day due to a new business area — their legacy system might hit performance ceilings. Traditional SQL databases were not built to handle exponential data growth. That's one of the biggest obstacles companies face when transitioning to BD. Your research must uncover these root causes and provide concrete justifications for adopting BD tools. The framework should include diagnostics, real examples, and response strategies that help organizations transition from "good enough" solutions to scalable, future-ready architectures.

Q2. How can user resistance be tackled effectively when introducing BD tools?

E: Overcoming user resistance requires more than introducing new systems — it demands

empathy, structure, and communication. Resistance often stems from a lack of understanding, fear of redundancy, or unfamiliarity with tools. A user-centric onboarding process must be central to the adoption phase, and onboarding programs should focus on practical use cases, not just theoretical training. This means segmenting users based on their openness to change, identifying their core concerns, and responding with targeted strategies. For example, a user accustomed to traditional SQL might hesitate to adopt Spark or DBT because of steep learning curves or perceived instability. Through structured interviews or surveys, you can ask users about their current frustrations, how often tools fail to deliver timely insights, and what support mechanisms they'd need to feel comfortable exploring new platforms. You might discover that resistance is not against the tool itself but against the lack of training or communication about the benefits. Your framework should guide organizations through this entire change process — from diagnostics, to communication plans, to training roadmaps — ensuring that users aren't left behind but feel supported throughout the transformation.

Q3. What types of questions would help determine if an organization is ready to adopt a new BDA initiative?

E: To assess readiness effectively, your framework should include a detailed questionnaire or readiness assessment form that touches on strategic, operational, and cultural aspects. Relevant questions might include:

- What are the current data tools in use and how are they perceived in terms of efficiency and limitations?
- Are business and IT stakeholders aligned in their expectations from data initiatives?
- What is the organization's track record with adopting new technologies?
- How are data volumes evolving, and do current tools handle them well?
- Are there defined success metrics for data projects?

Your framework could include a scoring model for these questions — allowing decision-makers to calculate an adoption readiness score. For instance, organizations scoring below a threshold might require preliminary work on cultural readiness or digital maturity before launching a BDA project. The advantage of this method is that it quantifies abstract sentiments and gives teams a tangible indicator of preparedness. This form can be embedded as a PDF or interactive module in the framework, acting as a gateway to more advanced stages. BD adoption must feel intuitive, with training based on real-world applications.

Q4. What should the second phase of implementation—technology selection—look like within the ADIF structure?

E: Phase 2 should be guided by structure, clarity, and adaptability. The process should begin by categorizing technologies by functional domains, such as:

- ETL/ELT (e.g., DBT, Apache Nifi),
- Data storage (e.g., Snowflake, Hadoop, AWS S3),
- Orchestration (e.g., Airflow, Prefect),
- Analytics & Visualization (e.g., Power BI, Tableau),
- Machine Learning (e.g., Databricks, Vertex AI).

For each category, your framework should present not just tool names but key attributes: open-source vs. commercial, licensing costs, integration capabilities, vendor support, ease of learning, and performance in real-world use cases. The list should help organizations filter technologies based on insights collected during the adoption phase. For example, if an organization identified slow processing speed and lack of cloud integration as major pain points, they can use those filters to narrow down choices. This process empowers users to make informed and contextual decisions rather than defaulting to the most popular or hyped technology.

Q5. What does the strategic implementation phase consist of, and how can ADIF structure it?

E: The strategic implementation phase must be treated as a full project plan, divided into well-defined steps that mirror best practices from project management. The stages might include:

1. Kick-off & Strategic Alignment — confirm executive buy-in, define business goals, align stakeholders.
2. Technology Selection & Proof of Concept — select tools based on diagnostics, run a PoC in a controlled environment.
3. Pilot Deployment — roll out the chosen tool(s) in a small, low-risk domain.
4. Full Implementation — expand usage across relevant departments with feedback loops.
5. Post-Implementation Review — assess against success metrics, gather user feedback, plan for optimization.

Each phase should specify roles (e.g., technical leads, business owners), deliverables (e.g., training guides, architecture diagrams), timelines, and risk mitigation strategies. Your framework should provide templates or guides to help project managers map out responsibilities and monitor progress. Having a built-in strategic roadmap makes the framework not only theoretical but also operationally applicable, increasing the likelihood of successful and sustainable BDA adoption. Scalability, governance, and adaptability are key enablers of success in modern data ecosystems.

Q6. How should ADIF deal with fast-changing technologies like AI integration?

E: One of the strengths of your framework should be its capacity to evolve with the

ecosystem. Emerging technologies, especially in AI, are fundamentally reshaping how organizations access, process, and derive value from data. For instance, the rise of natural language interfaces that allow business users to ask questions without writing SQL opens entirely new adoption paths. ADIF should acknowledge that digital maturity varies significantly between institutions — some are ready to experiment with GPT-based data querying, while others are still adapting to cloud platforms. Companies often underestimate cloud costs so if you don't plan carefully, the operational expenses can quickly spiral out of control The framework should recommend adaptive strategies, such as continuous skills training, experimentation labs, and governance guidelines for adopting emerging tools. At the same time, it should emphasize governance, validation, and trust — as even the most advanced AI systems are only as good as the data and human context behind them. Encouraging a balance between innovation and risk management will position ADIF as a responsible and forward-looking guide for long-term digital growth.

Q7. What additional outputs can ADIF provide to aid its adoption?

E: For ADIF to be truly effective and user-friendly, it should offer a suite of practical deliverables alongside the theoretical structure. Some key outputs could include:

- A diagnostic questionnaire or self-assessment tool to measure readiness and identify gaps.
- A PowerPoint presentation kit to help change agents communicate the value of ADIF to stakeholders.
- A technology catalog categorized by functionality and evaluated with filtering logic based on organizational needs.
- A project roadmap template with editable phases, timelines, and accountability fields.

By including these assets, you transform ADIF into a living framework — not just a set of ideas, but a toolkit that professionals can pick up and use directly. These materials reduce friction in adoption, guide conversations, and enable organizations to tailor ADIF to their context. The more actionable and accessible the framework becomes, the higher its potential impact on real organizational transformations.

Appendix D – Interview 3 Transcript

03/2025

Interviewee: Expert

Q1: Considering the three-phase plan previously discussed, what's the feedback of the end result?

E: From what you've shown me, it's clear that you've taken the previously suggested three-phase plan and effectively translated it into a structured approach. You were able to concentrate each stage into clear components, which shows that you're not just understanding the flow conceptually, but also managing to operationalize it. The fact that you've laid out each phase — beginning with user adoption, followed by technology evaluation, and concluding with a proof of concept — demonstrates a logical sequence. Now that you've outlined the framework's structure, the next logical step is to develop the content within those phases. Overall, the structure looks sound and you're ready to start putting it into action.

Q2: In Phase 1, I created a user adoption questionnaire to assess tasks, tool usage, pain points, expectations, and change management perspectives. Do you think this is sufficient?

E: Yes, I think it's more than sufficient to support an initial understanding of user sentiment and the barriers to adoption. What you've created enables an organization to

perform a kind of diagnostic before engaging with any new BDA initiative. You've included general profiling questions (e.g., tasks performed, tools in use), but also targeted issues like pain points, which can reveal operational bottlenecks or friction points in everyday usage. Additionally, incorporating expectations and attitudes toward change — particularly around new technologies — is essential for successful onboarding. You're not overcomplicating the process, which is good. In fact, you're offering a lean but meaningful way to perform a readiness check. This initial layer serves both as a temperature check and as a guide for tailoring the remaining phases. I'd say this is a very strong foundation for Phase 1.

Q3: For Phase 2, I built a pseudo-evaluation framework for technology selection using six criteria: scalability/performance, integration/interoperability, security/compliance, usability, community/support, and licensing/cost. Does this evaluation matrix make sense?

E: Absolutely. You've managed to cover the most relevant technical and strategic considerations that an organization in the financial sector would typically weigh when selecting BDA technologies. Starting with scalability and performance ensures the solution can handle growing data volumes and latency-sensitive use cases. Integration and interoperability help ensure that the tool can function seamlessly within existing IT environments, which are often fragmented in financial institutions. Security and compliance, especially in the context of financial regulation (GDPR, PSD2, Basel III), are critical. Usability, documentation, and training availability reflect your attention to user experience — which ties nicely back to Phase 1. The inclusion of licensing and support models is also smart, especially because many institutions weigh the risks of open-source versus commercial support differently. Altogether, these dimensions give your framework credibility and realism. The matrix approach you're proposing helps quantify qualitative assessments and assists in prioritizing technologies based on organizational goals.

Q4: So the scorecard table should be just a suggestion, and not fixed?

E: Exactly. One of the key points to remember is that different organizations have different priorities depending on their budget, team skillsets, risk tolerance, and business goals. For example, a startup bank might prioritize open-source flexibility and cost, while a legacy institution might put more weight on compliance and vendor support. If your scorecard has fixed weights — say, assigning 20% to performance across the board — it risks misrepresenting what matters most in each context. Instead, your framework should allow users to define their own weighting scheme, either manually or through a set of guiding questions. This level of configurability will increase the adaptability of your model and make it more likely to be adopted in real-world settings.

Q5: Moving on to Phase 3 – the Proof of Concept (PoC) – I structured it to include goals, technologies used, expected outcomes, challenges, methodology, implementation steps, onboarding, testing, governance, performance, and concluding remarks. Is this structure solid?

E: That's a comprehensive and very well-rounded structure. You've essentially designed a mini-project template that can be replicated across organizations. The way you've broken it down — from establishing the executive summary and objectives to defining methodologies and governance layers — shows a clear understanding of how PoCs work in practice. Highlighting onboarding, training, and even measuring before-and-after impacts (like improved processing time or better fraud detection) will make your framework not only more robust but more actionable. The only caveat I would give is with respect to the benchmarking section. It's not that it's wrong to include it — in fact, it could add immense value — but you have to be mindful of the complexity involved. Gathering robust, comparable performance metrics requires controlled environments and often infrastructure that isn't always available for pilot projects. Also the architecture has to

evolve with the business, not the other way around. So yes, keep the structure, but consider labeling certain elements like benchmarking as optional or advanced components within the PoC.

Q6: Could that benchmarking section be reframed as a suggestion for future research?

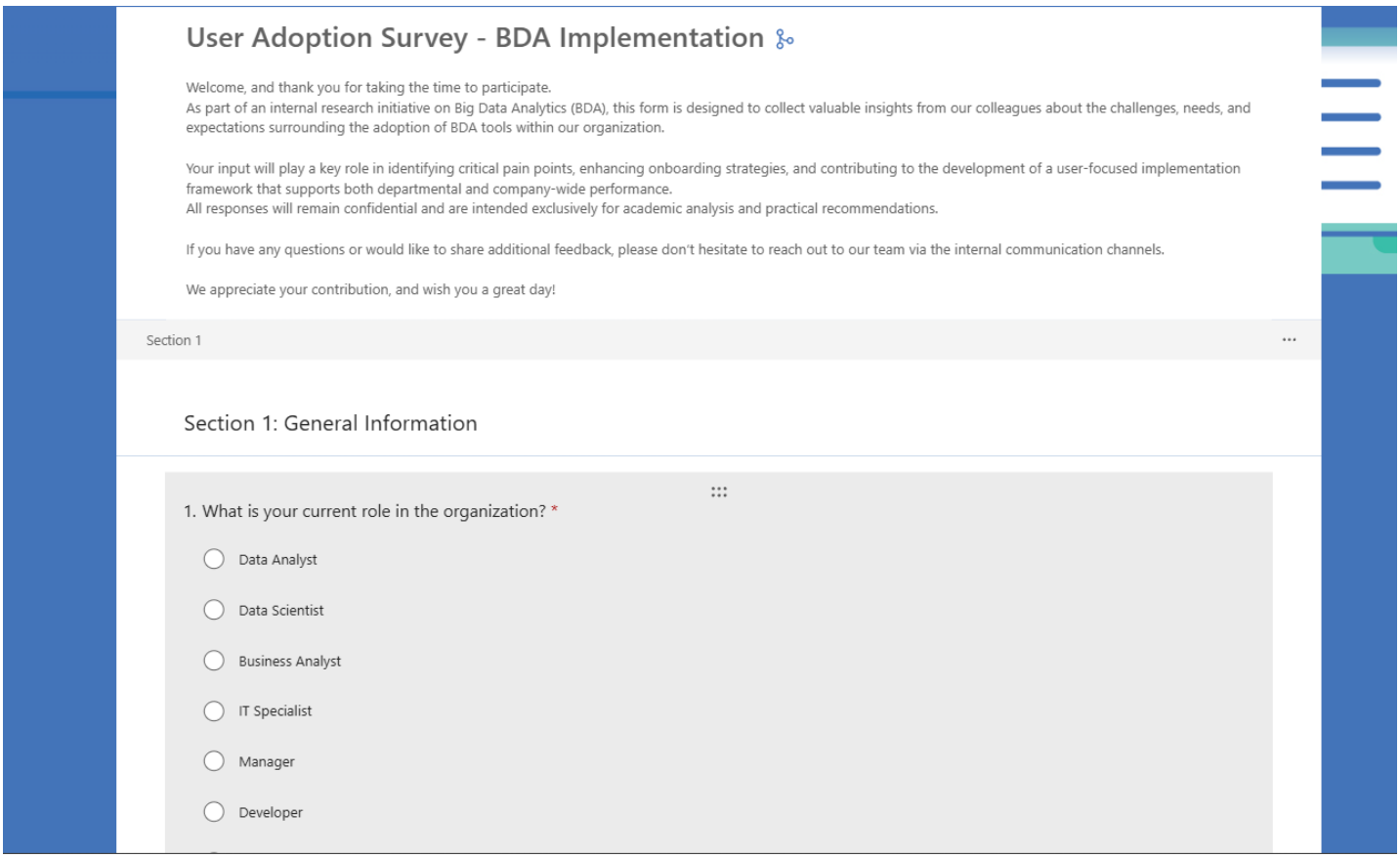
E: Yes, and that would be a smart way to handle it. Benchmarking, when done well, provides empirical evidence of a solution's value — which is especially useful in persuading stakeholders. However, given the limitations that many organizations face in setting up test environments, collecting accurate metrics, or even interpreting them correctly, you might risk overextending the implementation complexity. By framing it as a recommendation for future research or as an advanced optional module, you protect the integrity of your framework while still showing a forward-thinking mindset. That kind of academic humility is often well received in thesis evaluations.

Q7: What about a success metrics dashboard— showing things like execution time, data accuracy, user adoption, etc.? Would it make sense to include this in the framework?

E: That's a very smart addition. Including a visual representation of success metrics not only gives credibility to your proposal but also aligns it with modern BI practices. It allows stakeholders to track the outcomes of implementation and provides a feedback loop into the framework. However, as with benchmarking, turning it into a real-time monitoring tool might be overly ambitious unless you have access to operational systems that can continuously feed data into the dashboard. In most cases, what works better is to treat it as a snapshot mechanism — a way to compare baseline conditions (before implementation) with conditions post-implementation, after a few weeks or months. It's incredibly valuable to visualize things like adoption growth, data quality improvements,

or performance gains. But make sure you position it as an assessment tool, not as an active performance management system.

Appendix E – User Adoption Survey[1]



[1] *Link to the survey:* *https://forms.office.com/Pages/DesignPageV2.aspx?origin=NeoPortalPage&subpage=design&id=GIvjszm6sUKsGjcltUihutjvwygwKU9GtyUF9MhU6dxUQzVTNTEwTDU2OEpJQjFQTEpXWlVTQTBNVC4u&branchingelementid=rd92aa403830b4bcb9740155483415edc&analysis=false*

- ◯ Other

2. How frequently do you work with data-related tools in your daily tasks? *

- ◯ Daily
- ◯ Several times per week
- ◯ Sometimes
- ◯ Rarely
- ◯ Once a month
- ◯ Never

3. Which of the following BDA tools or technologies are you currently using? (Select all that apply) *

- ☐ SQL Databases (e.g., MySQL, PostgreSQL, SQL Server)
- ☐ Big Data Platforms (e.g., Hadoop, Spark)
- ☐ Cloud Analytics (e.g., AWS, Azure, Google BigQuery)
- ☐ Business Intelligence Tools (e.g., Power BI, Tableau)
- ☐ Machine Learning Platforms (e.g., TensorFlow, Scikit-Learn)
- ☐ Other

4. If you chose 'Other', please specify below: *

Enter your answer

Section 2 ...

Section 2: Identifying Pain Points & Bottlenecks

5. What are the biggest challenges you face with your current data tools? (Select all that apply) *

- ☐ Performance issues (slow processing, long query times)
- ☐ Data accessibility (difficulty retrieving or integrating data)
- ☐ Lack of training or expertise
- ☐ Lack of automation (manual, repetitive tasks)
- ☐ Poor user interface or user experience
- ☐ Other

6. Have you encountered resistance from colleagues or management when adopting new data technologies? *

- ◯ Yes, frequently
- ◯ Yes, occasionally

- ◯ No, but I have concerns about adoption
- ◯ No, adoption is generally smooth

7. If yes, what are the primary reasons for this resistance? *

- ◯ Lack of perceived value in the new tools
- ◯ Fear of job disruption or change in responsibilities
- ◯ Insufficient training or onboarding support
- ◯ Preference for traditional methods
- ◯ Other

8. How would you rate the effectiveness of current training and support provided for BDA adoption? *

- ◯ Excellent
- ◯ Good
- ◯ Average
- ◯ Very good
- ◯ Poor

Section 3

Section 3: Expectations from New Technology

9. What features or improvements would make you more likely to adopt new BDA tools? (Select all that apply) *

- ☐ User-friendly interfaces
- ☐ Faster processing times
- ☐ Better integration with existing systems
- ☐ More automation and AI-driven insights
- ☐ More training and documentation
- ☐ Other

10. In your opinion, what is the most important factor for ensuring the successful adoption of BDA tools? *

- ◯ Strong leadership support and strategic alignment
- ◯ Clear ROI (return on investment) and business impact
- ◯ Hands-on training and onboarding programs
- ◯ Gradual transition with minimal workflow disruption

- ◯ Peer mentorship and knowledge sharing

Section 4 ...

Section 4: Measuring Success & Change Management

11. How would you define success in the adoption of new BDA tools? *

- ◯ Increased efficiency in data analysis and reporting
- ◯ Higher adoption rate across teams
- ◯ Reduced manual effort and increased automation
- ◯ Improved decision-making through better data insights
- ◯ Other

12. How often would you like to receive updates and training on new BDA tools? *

- ◯ Annually
- ◯ Quarterly
- ◯ Monthly
- ◯ On-demand

13. What format do you prefer for training sessions? (Select all that apply) *

13. What format do you prefer for training sessions? (Select all that apply) *

- ◯ In-person workshops
- ◯ Virtual training sessions
- ◯ Self-paced online courses
- ◯ Short tutorial videos and guides
- ◯ Team sessions with an expert
- ◯ One-on-one mentoring sessions

Section 5 ...

Section 5: Final Insights & Suggestions

14. Do you have any concerns or suggestions regarding the adoption of BDA tools in your organization? *

Enter your answer

15. Would you be interested in participating in further workshops, pilot programs, or discussions on improving BDA adoption? *

- ◯ Yes
- ◯ No

Appendix F – Model Example of a Technology Selection Matrix

Technologies utilized for the example: Apache Spark; Snowflake; Microsoft Power BI.

Technology Evaluation & Comparison

Criteria	Weight (%)	Apache Spark[2]	Snowflake[3][4]	Microsoft Power BI[5]
1. Scalability & Performance	20%	High (3)	High (3)	Medium (2)
Data Volume Handling		Designed for large-scale data processing.	Handles massive datasets efficiently.	Suitable for moderate datasets.
Processing Capability		Supports both batch and real-time processing.	Optimized for batch processing; real-time with additional configurations.	Primarily batch processing; real-time with limitations.
Latency & Throughput		Low latency with high throughput.	Low latency; high throughput.	Moderate latency; suitable for interactive reports.
2. Integration & Interoperability	15%	High (3)	High (3)	High (3)

[2] AltexSoft. (n.d.). *Apache Spark: Pros and Cons*. https://www.altexsoft.com/blog/apache-spark-pros-cons (*The Good and the Bad of Apache Spark*, n.d.)

[3] Acceldata. (2023). *Snowflake vs Databricks: Performance and scalability analysis*. https://www.acceldata.io/blog/snowflake-vs-databricks-performance-and-scalability-analysis (*Snowflake vs. Databricks: A Performance and Scalability Comparison | Acceldata*, n.d.)

[4] Data Ideology. (n.d.). *Snowflake Data Warehouse Advantages.* https://www.dataideology.com/snowflake-data-warehouse-advantages/ (*Snowflake Data Warehouse Advantages - Data Ideology*, n.d.)

[5] New Horizons. (n.d.). *10 Benefits of Power BI for Your Business*. https://www.newhorizons.com/resources/blog/power-bi-benefits (*Top 10 Benefits of Using Power BI for Data Analysis - New Horizons - Blog | New Horizons*, n.d.)

Financial IT Compatibility		Integrates with various data sources and platforms.	Seamlessly integrates with major data platforms.	Excellent integration with Microsoft products; connectors available for other sources.
APIs & Extensibility		Rich API support; highly extensible.	Comprehensive APIs; extensible.	Extensive APIs; customizable.
Cross-Platform Support		Runs on-premises, cloud, and hybrid environments.	Cloud-native; supports hybrid through partners.	Cloud and on-premises support.
3. Security & Compliance	20%	High (3)	High (3)	High (3)
Regulatory Compliance		Compliant with major standards; requires configuration.	Built-in compliance with GDPR, HIPAA, etc.	Complies with major standards; depends on deployment.
Data Encryption & Privacy		Supports encryption; privacy controls depend on setup.	End-to-end encryption; robust privacy features.	Offers encryption; privacy features depend on configuration.
Auditability & Logging		Provides logging; audit capabilities depend on implementation.	Comprehensive auditing and logging features.	Detailed logging; auditing varies by setup.
4. Usability & Adoption Readiness	15%	Medium (2)	High (3)	High (3)
Ease of Use		Requires technical expertise.	User-friendly interface; minimal coding.	Intuitive interface; suitable for

				non-technical users.
Training & Documentation		Extensive documentation; steep learning curve.	Comprehensive resources; easier learning curve.	Abundant tutorials and community support.
Community & Vendor Support		Large open-source community; varied support.	Strong vendor support; active community.	Robust support from Microsoft; large user community.
5. Cost & Licensing Model	15%	High (3)	Medium (2)	Medium (2)
Open-source vs. Commercial		Open-source; free to use.	Commercial; subscription-based.	Commercial; subscription-based.
Total Cost of Ownership (TCO)		Lower TCO; infrastructure costs apply.	Higher TCO; includes support and maintenance.	Moderate TCO; varies by usage.
Vendor Lock-in Risks		Low; open-source flexibility.	Potential lock-in; proprietary platform.	Moderate; integrates best within Microsoft ecosystem.
6. Strategic Alignment	15%	High (3)	High (3)	High (3)
Industry Adoption		Widely adopted across industries, including finance.	Growing adoption in financial services.	Extensive use in finance for BI and reporting.
Business Impact		Enhances data processing and analytics capabilities.	Improves data warehousing and analytics.	Facilitates data visualization and decision-making.

Future Adaptability		Highly adaptable; supports new technologies.	Scalable and adaptable to future needs.	Regular updates; integrates emerging technologies.

Scoring:

- High = 3 points
- Medium = 2 points
- Low = 1 point

Calculation:

- **Apache Spark**: (20% × 3) + (15% × 3) + (20% × 3) + (15% × 2) + (15% × 3) + (15% × 3) = **2.85**
- **Snowflake**: (20% × 3) + (15% × 3) + (20% × 3) + (15% × 3) + (15% × 2) + (15% × 3) = **2.95**
- **Microsoft Power BI**: (20% × 2) + (15% × 3) + (20% × 3) + (15% × 3) + (15% × 2) + (15% × 3) = **2.75**

Technology Selection Result: Snowflake.

Appendix G – Model Example of Proof of Concept (PoC) Report

Proof of Concept (PoC) Report

Date: [Insert Date]
Prepared by: [Your Name]
Organization: [Company/Institution Name]

---

1. Executive Summary

- **Objective of PoC:**
  Summarize what this PoC aims to validate (e.g., ADIF's impact on financial BDA adoption).
- **Key Technologies Tested:**
  List tools used, e.g., Snowflake, DBT, Power BI.
- **Expected Outcomes:**
  Describe intended benefits (e.g., faster processing, increased adoption).

---

2. Scope & Use Case

- **Business Problem Addressed:**
  What challenges exist in BDA adoption within financial firms?
- **Target Data & Systems:**
  Describe datasets used (e.g., transaction logs, risk models).
- **Test Environment:**
  Cloud-based, on-premise, hybrid setup?

---

3. Methodology

3.1 Baseline Assessment

- **Current pain points:**
  What inefficiencies exist in data workflows?
- **Performance benchmarks:**
  Pre-ADIF system metrics (e.g., query time, user engagement).

3.2 ADIF Implementation

- **Technologies deployed:**
  Describe how ADIF was introduced (e.g., DBT pipelines).
- **User onboarding process:**
  How were users trained and engaged?

3.3 Testing & Monitoring

- **A/B Testing Approach:**
  Compare legacy vs. ADIF-enhanced workflows.
- **Monitoring Period:**
  e.g., 4 weeks of performance tracking.

---

4. Governance Policies & Best Practices

4.1 Data Governance Policies

i. **Data Quality Standards:**

- **Accuracy:** All ingested data validated before processing.

- **Consistency:** Standardized date formats across datasets.

ii. **Security & Compliance:**

- **Access Control:** Role-based permissions for analysts & engineers.
- **Encryption:** End-to-end encryption for financial compliance (GDPR, Basel III).

iii. **Data Ownership & Stewardship:**

- Assign Data Stewards to track transformations & lineage.

4.2 Best Practices for ADIF Implementation

iv. **Naming Conventions & Documentation:**

- Use clear table & column names (transaction_log, risk_score).
- Maintain ETL pipeline documentation in Git repositories.

v. **Performance Optimization:**

- Implement caching & indexing for faster queries.
- Reduce redundant transformations in DBT workflows.

---

5. Results & Analysis

Metric	Before ADIF	After ADIF	% Improvement
Query Execution Time (ms)	**1200**	**800**	**33.3%**
ETL Processing Time (mins)	**45**	**30**	**33.3%**
User Adoption Rate (%)	**40**	**75**	**87.5%**
Strategic Alignment Score	**60**	**85**	**41.6%**
Data Processing Speed (GB/sec)	**1.2**	**2.5**	**108.3%**
Security Compliance Score	**75**	**90**	**20%**

Observations:

- Query execution & ETL processing significantly improved.
- User adoption nearly doubled, confirming better onboarding & usability.
- Security & compliance strengthened post-implementation.

---

6. Knowledge-Sharing & Continuous Learning

6.1 Post-PoC Learning Sessions

1. **Organize monthly knowledge-sharing sessions to discuss:**
    a) Lessons learned from PoC findings.
    b) Best practices for using ADIF in real-world financial analytics.
    c) Common pitfalls and troubleshooting strategies.

6.2 Internal Documentation & Collaboration

2. **Create a dedicated knowledge base for ADIF:**
    a) Implementation guidelines
    b) Success stories from PoC
    c) FAQs & troubleshooting resources

6.3 Community-Driven Learning

3. **Encourage peer mentoring by:**
    - Assigning subject-matter experts to guide new users.
    - Hosting internal workshops & case study discussions

---

7. Conclusion & Recommendations

- **Final Verdict:** ADIF successfully improves BDA adoption in financial firms.
- **Next Steps:** Expand ADIF to full-scale deployment with governance policies & knowledge-sharing strategies.
- **Refinements Needed:**
    - **Enhance data compliance monitoring for real-time tracking.**
    - **Establish long-term performance benchmarking.**

Approval & Sign-Off:
Reviewed by: [Stakeholder Name]
Date: [MM/DD/YYYY]

Declaration of generative AI usage

During the preparation of my written thesis, **Big Data Analytics: An Implementation Framework for the Portuguese Financial Sector**, ChatGPT by OpenAI was used for occasional language refinement, summarization of selected interview content, assistance in content structuring and identification of potential limitations on proposed solutions. Additionally, Turboscribe by TurboScribe was used to assist in verifying the accuracy of transcript content against audio recordings and in highlighting potential valuable insights from transcripts.

The prompts used are listed at the end of the document in the Prompts List section. All outputs were reviewed and edited by me, and I take full responsibility for the content of the work presented.

I also declare that I am aware of and respect the Artificial Intelligence Rules of Conduct of Católica Porto Business School.

Prompts List

This section includes a curated selection of the prompts used throughout the development of this dissertation. The following examples reflect how generative AI was utilized as a complementary tool.

1. Identify potentially relevant themes emerging from this interview section.
2. Suggest a more structured way to present this idea.
3. Recommend more impactful or precise terminology to express this concept in an academic context.
4. What potential limitations or drawbacks should be considered when presenting this proposed solution.
5. Propose a clearer way to phrase this sentence while maintaining its original meaning.
6. Exemplify an appropriate technique to connect this example or case.

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