UNIVERSIDADE CATÓLICA PORTUGUESA

The role of Big Data Analytics in Omnichannel retailers

The case study of an Iberian-based Utility

Jorge Rodrigo do Vale Marques da Silva

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This accomplishment is as much theirs as it is mine.

"Without data, you're just another person with an opinion."

W.Edwards Deming

Abstract

The increasing digitalisation of the energy sector has led many companies to adopt Artificial Intelligence (AI) and Big Data Analytics (BDA) tools to enhance Operational Efficiency (OE). This study investigates how these technologies are practically employed within a leading Iberian energy company, specifically exploring their roles in streamlining operational processes and supporting decision-making through digital channels. It seeks to bridge the gap between theory and practice by examining how AI and BDA tools can be effectively applied to optimise internal operations, improve service delivery, and strengthen strategic agility in the energy sector.

To achieve this, a qualitative case study approach was adopted, comprising semi-structured interviews with professionals from an Iberian-based utility actively involved in AI, BDA, and OE initiatives, complemented by document analysis of internal and industry materials.

Findings highlight the application of AI and BDA in digital self-service platforms, customer support automation, operational dashboards, and Robotic Process Automation (RPA). Additionally, asset and facilities management are addressed through a dedicated platform, with IoT integration enabling real-time monitoring and anomaly detection.

Despite these advancements, the study also identifies several limitations, including regulatory and data privacy constraints, limited predictive maintenance capabilities, high IoT deployment costs, and integration challenges. These insights contribute to a deeper understanding of the practical barriers and opportunities related to AI and BDA adoption in energy utilities, offering guidance for future implementations.

Keywords: Artificial Intelligence, Big Data Analytics, Operational Efficiency

Resumo

A crescente digitalização do setor energético tem levado muitas empresas a adotar ferramentas de Inteligência Artificial (IA) e Big Data Analytics (BDA) com o objetivo de melhorar a Eficiência Operacional (EO). Este estudo investiga como essas tecnologias são aplicadas na prática por uma empresa de energia de referência na Península Ibérica, explorando especificamente os seus papéis na otimização de processos operacionais e no suporte à tomada de decisão através de canais digitais. Pretende-se, assim, colmatar a lacuna entre a teoria e a prática, examinando como as ferramentas de IA e BDA podem ser eficazmente utilizadas para otimizar operações internas, melhorar a prestação de serviços e reforçar a agilidade estratégica no setor da energia.

Para tal, foi adotada uma abordagem qualitativa de estudo de caso, composta por entrevistas semiestruturadas com profissionais de uma empresa ibérica diretamente envolvidos em iniciativas de IA, BDA e EO, complementada por análise documental de materiais internos e do setor.

Os resultados evidenciam a aplicação de IA e BDA em plataformas digitais de self-service, automação do apoio ao cliente, dashboards operacionais e Robotic Process Automation (RPA). A gestão de ativos e instalações também é abordada através de uma plataforma dedicada, com integração de IoT para monitorização em tempo real e deteção de anomalias.

Apesar desses avanços, o estudo identifica também várias limitações, incluindo restrições regulatórias e de privacidade de dados, capacidades limitadas de manutenção preditiva, elevados custos de implementação de IoT e desafios de integração. Estas perceções contribuem para uma compreensão mais aprofundada dos obstáculos e oportunidades práticos associados à adoção de IA e BDA por empresas de energia, oferecendo orientações úteis para futuras implementações.

Palavras-chave: Inteligência Artificial, Big Data Analytics, Eficiência Operacional

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Introduction

Across various industries, AI and BDA have emerged as critical enablers of operational efficiency. Their capacity to automate complex workflows, enhance predictive capabilities, and streamline decision-making processes has transformed sectors such as finance, healthcare, and retail (Davenport & Ronanki, 2018; Wamba et al., 2020). These technologies reduce manual effort, improve resource allocation, and support agile operations. In the energy sector—characterised by complex infrastructure, the need for real-time responsiveness, and fluctuating demand—the strategic adoption of AI and BDA offers significant potential for enhancing operational performance at scale.

Although the overarching theme of this research lies in understanding the role of BDA within omnichannel environments, the research question— *"How can AI and BDA impact operational efficiency in the energy sector?"*—was deliberately chosen to explore how data-driven and AI technologies operate in a critical, infrastructure-dependent industry. The energy sector presents a particularly compelling case due to its pressing need for digital transformation, its high operational complexity, and its growing reliance on decentralised and real-time data streams. By shifting the focus to this sector, the study seeks to provide grounded insights into how AI and BDA tools are being used not only to improve customer-facing processes but also to streamline internal operations, automate routine tasks, and optimise asset management. This approach offers a valuable lens through which to understand the practical enablers and limitations of BDA in large-scale, regulated environments—insights that are highly transferable to omnichannel strategies in other industries, particularly where operational agility and service consistency are critical. The digital transformation wave has thus positioned AI and BDA not merely as innovation tools but as fundamental pillars for competitiveness and resilience in increasingly volatile environments (Mikalef et al., 2020; Chen et al., 2022). The energy sector stands at a pivotal point in its digital transformation journey, where the deployment of AI and BDA is no longer optional but imperative. Unlike other industries, energy utilities must navigate a uniquely complex environment marked by stringent regulation, decentralised infrastructures, and long asset life cycles, all while responding to rising expectations for sustainability, transparency, and digital accessibility (Sarker et al., 2022). At the same time, the integration of renewables, the spread of smart technologies, and the diversification of services are generating unprecedented volumes of data and increasing system complexity (Zhou et al., 2016).

In this evolving landscape, AI and BDA offer promising capabilities to streamline operations and enable more intelligent, proactive forms of customer and asset management (Chatterjee et al., 2021; Huang et al., 2021). Yet, despite growing interest, much of the literature continues to emphasise potential use cases rather than real-world implementations. There is limited understanding of how these technologies are applied in operational contexts and what conditions enable or hinder their success (George et al., 2014; Popovič et al., 2018; Haenlein et al., 2022).

This research addresses that gap by exploring the question: “How can AI and BDA tools be used in the energy sector to improve operational efficiency?” Using a qualitative case study approach, it investigates how an Iberian-based utility is leveraging these technologies across its digital ecosystem—to enhance customer interaction, automate processes, and support data-driven decision-making (Wamba et al., 2017). The study draws on semi-structured interviews with professionals involved in AI, BDA, and operational projects, complemented by internal documentation to triangulate and enrich the findings.

These objectives are guided by prior research that links BDA capabilities to organisational performance and strategic agility (Mikalef et al., 2020), while also highlighting the technical and organisational barriers to implementation in complex environments (Kache & Seuring, 2017).

Ultimately, the findings show that the value of AI and BDA extends beyond technology itself. Their success depends on agile systems, cross-functional collaboration, and a customer-centric culture that fosters intelligent, data-informed service delivery (Kumar et al., 2021; Wamba-Taguimdje et al., 2020). Structurally, the investigation is organised into clearly delineated sections: (1) a literature review outlining theoretical perspectives and current applications of AI and BDA within the energy sector; (2) a brief explanation on the methodology employed and how data was collected (4) a detailed results section incorporating expert interviews with professionals from the Iberian-based utility, along with document analysis to triangulate and contextualise the findings; (4) a discussion integrating empirical results with literature insights; (5) a concluding section that synthesises key research insights and provides strategic recommendations.

Chapter 1

1. Literature Review

1.1 Context

The rising complexity of the energy sector—marked by decentralisation, digitalisation, and evolving consumer demands—has accelerated the adoption of AI and BDA tools. These technologies are now viewed as strategic enablers for improving operational efficiency, with key applications in automation, predictive analytics, and asset management across utility infrastructures.

1.2 AI and BDA: Concepts and Importance

AI encompasses the development of systems capable of simulating human cognitive functions, such as reasoning, problem-solving, and learning (Russell & Norvig, 2021). In broad organisational contexts, AI has been instrumental in automating routine tasks, improving decision accuracy, and delivering personalised services across sectors ranging from healthcare to finance (Haenlein et al., 2022). BDA, in turn, refers to the collection, integration, and analysis of voluminous and heterogeneous datasets to uncover insights, correlations, and patterns that would otherwise remain hidden (Gandomi & Haider, 2015). Together, these technologies constitute the core of modern digital intelligence.

In the energy sector specifically, the deployment of AI and BDA has evolved from a promising frontier to an operational imperative. Their relevance is magnified by the sector's growing complexity—marked by decentralised infrastructures, renewable energy integration, real-time grid balancing, and increasingly digital customer expectations. AI technologies are being implemented in areas such as predictive maintenance, demand forecasting and real-time pricing strategies (Zhou et al., 2016; Chatterjee et al., 2021). For instance, intelligent algorithms now assist in monitoring equipment health and detecting anomalies in consumption patterns, thereby minimising downtimes and enhancing reliability.

BDA, on the other hand, facilitates strategic agility and operational responsiveness by enabling critical insights into consumer behaviour, forecasting, and asset performance. Particularly in smart grid environments, BDA supports real-time data visualisation, adaptive load control, and enhanced integration of decentralised energy resources.

Although these tools are widely used across sectors to improve process efficiency and customer engagement (George et al., 2014; Chen et al., 2012), their application in energy utilities carries distinct operational and strategic implications. For example, machine learning models in this domain must manage heterogeneous data sources from smart meters, sensors, and operational systems, while also navigating regulatory constraints and infrastructure limitations. Natural Language Processing (NLP) is increasingly being employed to automate the interpretation of customer service interactions, thereby enhancing responsiveness and reducing human workload (Sheng et al., 2021).

The convergence of AI and BDA has given rise to intelligent energy management systems that adapt dynamically to real-time conditions. Given the These systems not only improve energy forecasting—studies report a reduction in prediction errors by up to 10% (Zhang et al., 2022)—but also enhance consumer satisfaction by offering targeted, timely, and relevant interventions.

From smart home optimisation to personalised tariff recommendations, AI-BDA solutions are driving a new era of service personalisation.

Ultimately, the strategic value of AI and BDA in the energy industry lies in their dual capacity to foster operational excellence and enrich customer experience. As energy firms face mounting pressure to deliver sustainable, responsive, and cost-effective services, these technologies enable a shift from traditional utility models to proactive, data-driven, and customer-centric ecosystems.

1.3 AI Driven Systems and Customer Service Automation

AI has transformed the way companies interact with customers, enabling hyper-personalised experiences through tools such as Next Best Action (NBA) and Next Best Offer (NBO). These systems leverage real-time behavioural data, contextual signals, and predictive analytics to deliver the most relevant message, product, or interaction at a given moment. As highlighted by Huang and Rust (2021), AI empowers firms to move from broad segmentation strategies to individualised engagement, enhancing customer satisfaction and increasing the effectiveness of marketing and service interventions. NBA focuses on identifying the most appropriate action to enhance the customer journey (e.g. suggesting an energy audit or plan change), while NBO prioritises the most relevant product or service to offer (e.g. dynamic tariff or solar panel installation).

In sectors such as telecommunications, retail, and increasingly in energy, NBA and NBO models have demonstrated improvements in customer retention, satisfaction, and revenue generation by aligning offers with real-time customer needs (Chatterjee et al., 2021). In the energy sector, these tools help tailor recommendations such as energy usage optimisations, tariff switching, or investments in smart home equipment, empowering customers with informed choices.

Despite the growing adoption of these tools, their successful implementation relies on high-quality data integration, customer segmentation models, and continuous model training. However, studies show that properly implemented AI recommendation engines can drive up to 30% increases in cross-selling rates and reduce churn by up to 25% (Wamba-Taguimdje et al., 2020).

Given the shifting dynamics in consumer expectations and increased competition in the energy sector, firms face an imperative to differentiate through advanced AI-driven personalisation and predictive capabilities. Recent studies highlight the necessity for energy providers to adopt sophisticated technologies that anticipate customer needs, provide individualised recommendations, and support informed consumer decisions around energy usage and management (Hajiheidari et al., 2023).

AI is increasingly used not only in customer-facing functions but also to enhance internal efficiency in energy utilities, particularly within software development. AI-based co-pilots assist with code generation, unit testing, and documentation, supporting agile methodologies, improving code quality, and reducing development time (Haenlein et al., 2022). In this context, such tools help overcome technical debt and accelerate digital adaptation. As Ransbotham et al. (2020) note, their integration fosters innovation by minimising repetitive tasks and freeing developers for strategic problem-solving. For instance, AI-powered chatbots represent one of the most tangible applications of AI for customer engagement, combining operational efficiency with enhanced service delivery. In decentralised, data-driven energy environments, chatbots support real-time communication, reduce response times, and lower the burden on support teams (Adam et al., 2021). Moreover, chatbot technology enhances proactive engagement by delivering tailored insights and energy-saving recommendations—critical features for driving loyalty in competitive markets (Adam et al., 2021).

Moreover, the application of AI-powered conversational agents has extended beyond customer service into internal business operations, where they serve as digital assistants to support employee productivity and decision-making. These tools, often built on large language models (LLMs) similar to ChatGPT, assist staff with tasks such as code generation, information retrieval, report writing, and content summarisation. As noted by Haenlein et al. (2022), internal AI assistants contribute to organisational agility by reducing cognitive load and allowing employees to focus on higher-value strategic tasks. Furthermore, Ransbotham et al. (2020) argue that these tools can democratise access to knowledge across departments, enhance development workflows, and accelerate innovation when properly integrated into daily operations. In knowledge-intensive sectors such as energy, where technical documentation and data management are critical, these systems can act as real-time copilots—providing operational support, ensuring knowledge continuity, and improving workforce responsiveness.

These tools are particularly effective in automating interactions and providing personalised assistance. AI further strengthens these capabilities through machine learning and predictive analytics, enabling more accurate and efficient operations (Gielen et al., 2019).

1.4 BDA tools for Energy Management

Across various sectors, BDA tools that provides interactive dashboards have become essential tools for organizations seeking to leverage data-driven decision-making, providing centralized and user-friendly platforms for visualizing complex datasets, monitoring performance metrics, and enhancing strategic planning. Such instruments improve organizational transparency, facilitate efficient resource management, and enhance customer satisfaction by delivering clear, accessible insights into operational and customer-related data. Interactive dashboards facilitate real-time monitoring, improve strategic planning, and enhance transparency (Knight, Pearson, & Brewerton, 2020).

These tools aggregate vast datasets into visual representations that support better decision-making. In the energy sector, dashboards are instrumental in managing consumption trends, identifying anomalies, and optimising load distribution (Zhang et al., 2022). Recent studies have shown that AI-powered systems can optimise the operation of household energy equipment—such as heating, cooling, and smart appliances—by learning from user habits and dynamically adjusting settings for efficiency and cost reduction (Zhang, Yang, & Wang, 2022).

Furthermore, the effective management of energy utilities' asset and facilities management, being vital to address due to their complexity and infrastructure dispersion. Energy utilities are responsible for maintaining a wide range of assets—from power plants and substations to administrative buildings and customer service facilities—which require continuous monitoring, timely maintenance, and optimal utilisation to ensure operational efficiency and reliability (Alonso & Sánchez, 2019). Digital asset management platforms enhance visibility, reduce downtime, and improve risk control (Frolov et al., 2021). When integrated with IoT and BDA, these systems enable predictive maintenance, cut operational costs, and support regulatory compliance (Zhou, Fu, & Yang, 2016), ultimately ensuring service continuity and improved customer satisfaction.

Like many energy providers operating across complex and decentralised infrastructures, the Iberian-based utility has adopted a digital asset management platform— "SmartFacilities" built upon NextBitt technology—to support maintenance planning, monitor asset performance, and track service-level compliance. This approach reflects broader sectoral trends, as highlighted by Frolov et al. (2021), who emphasise the role of such platforms in centralising operational data, facilitating anomaly detection, and enabling a gradual transition from preventive to predictive maintenance models.

Power BI and other similar platforms have become integral for energy companies seeking to simplify complex data flows. Li et al. (2022) found that real-time visualisation tools improved decision-making efficiency by 35% in grid operations. However, integrating dashboards with existing legacy systems remains a challenge, often requiring significant IT infrastructure upgrades and cross-departmental coordination (Jin et al., 2020). Addressing these critical factors through dedicated training programs, robust change management processes, and adequate infrastructure support remains essential for fully capitalizing on BDA tools (Jin et al., 2020; Meireles et al., 2022).

1.5 Challenges of AI and BDA in the Energy Sector

Despite the numerous advantages offered AI and BDA, their implementation across sectors faces persistent challenges. In industries such as healthcare, manufacturing, and retail, organisations encounter difficulties related to data quality, integration of disparate systems, talent shortages, and regulatory compliance (Haenlein et al., 2022). These challenges often impede the successful deployment of AI initiatives, with studies indicating that up to 70% of AI projects fail to scale due to operational and strategic misalignment (Chatterjee et al., 2021).

The energy sector presents a particularly complex implementation environment. Utilities typically operate on legacy IT infrastructures that were not designed to support modern AI or BDA technologies. These outdated systems inhibit the real-time data exchange required for AI-based optimisation and decision-making tools, complicating integration efforts (Zhou et al., 2016).

Furthermore, energy companies often struggle with data silos, making it difficult to ensure consistent, high-quality, and centralised data access for AI model training and deployment (Brock & von Wangenheim, 2019).

Another prominent challenge is organisational resistance to AI adoption. Employees often view automation tools, such as chatbots or RPA, as a threat to job security. This creates cultural barriers that must be addressed through strategic change management, transparency, and upskilling programmes (Brock & von Wangenheim, 2019; Belhadi et al., 2021). Moreover, firms report difficulties in sourcing professionals with expertise in AI, data science, and energy-specific applications, further delaying implementation timelines (Haenlein et al., 2022). Finally, the lack of scalable AI infrastructure represents a critical barrier to broader adoption. Studies show that energy companies often pilot AI initiatives without the necessary long-term digital strategy to integrate them across departments or geographies, resulting in fragmented outcomes and poor return on investment (ROI) (Zhang et al., 2022).

Despite these advancements, several persistent limitations emerge. The integration of AI and BDA tools remains constrained by legacy IT infrastructures, data silos and internal organisational resistance. Furthermore, the full realisation of benefits such as predictive personalisation, intelligent automation, and real-time visualisation still hinges on access to high-quality data, skilled personnel, and long-term strategic planning (Mikalef et al., 2018).

However, successful implementation of such tools is often hindered by integration challenges with legacy systems, insufficient training, and poor data quality management (Jin et al., 2020; Meireles et al., 2022). Recent insights from the Iberian-based utility support existing literature while highlighting practical uses of BDA in asset and facilities management. The adoption of the "*SmartFacilities*" platform shows the value of centralised data and automated maintenance, though limitations in predictive capabilities and IoT deployment reveal ongoing challenges related to cost and data fragmentation.

Chapter 2

2. Method and Data

2.1 Context

The purpose of this research is to explore how AI and BDA are being applied to improve internal efficiency in the energy sector. Specifically, the study focuses on the case of an Iberian-based utility, aiming to identify both strategic advantages and operational challenges from a practical business perspective and answering the research question: "How can AI tools and BDA be used in the energy sector to improve OE?"

2.2 Methodological Approach

To address the research objective, a qualitative methodological design was adopted, as it allows for the exploration of complex organisational practices and interpretations within their real-life context. Qualitative research is particularly suitable when the goal is to understand the meaning attributed to occurrences by those involved, in their natural organisational environment (Denzin & Lincoln, 2018).

The method selected was a single-case explanatory study, focused on an Iberian-based utility, which has already launched multiple AI and BDA initiatives in customer-facing and back-office domains. The case study approach is appropriate when the boundaries between the phenomenon and the context are not clear, and when the goal is to answer "how" and "why" questions regarding present organisational realities, which is aligned with the objective of this research in trying to fill the gap and provide an informed decision the explanatory nature of this design enables the researcher to gain deep insights into cause-effect relationships and implementation dynamics (Yin, 2018; Ridder, 2017).

This case study seeks not only to describe technological implementations but to explain their outcomes, perceived value, and associated challenges. The approach is also aligned with Eisenhardt and Graebner (2007), who advocate for case studies when examining emerging organisational capabilities in underexplored contexts—such as AI and BDA in energy utilities.

2.3 Data Collection

Data was collected through two rounds of semi-structured interviews with professionals directly involved in AI, BDA, digital interfaces, and customer experience at the utility. Interviewees included both strategic and technical profiles, allowing the research to integrate multiple perspectives and cover both customer-facing and operational applications.

These interviews were conducted via email, a format that allowed participants to reflect carefully on their responses and provide detailed, structured answers. This asynchronous method was particularly suitable given the interviewees' senior roles and busy schedules, enabling thoughtful insights without time constraints or interruptions.

The first round of responses explored core themes such as the digitalisation of customer services, chatbot development, RPA applications, and the use of AI for personalisation. A second follow-up round provided clarification on technical barriers, data integration practices, and the strategic application of visual analytics tools in facilities management through a specific internal platform.

A standard interview guide was used to ensure thematic consistency across both rounds. Despite being delivered in written form, the semi-structured nature of the questions allowed participants to elaborate freely and introduce new themes beyond the initial framework. This format enabled a rich understanding of practical implementations and internal dynamics surrounding AI and BDA tools within the company.

Interview	Department	Company Years	Date of Interview
1	Global Digital Customer Channels	6 years	30/01/2025
2	Data & Technical Management	8 years	21/02/2025

Table 1. Interviewees Information

Interview responses received via email were translated, adapted to a unified format, and integrated into a clean and structured document. Given the participants' extensive experience and organisational knowledge, the interviews yielded valuable practical insights on both current operations and future strategies.

2.4 Document and Data Analysis

Thematic analysis, following the approach by Braun and Clarke (2006), was employed to examine the interview data. This method involves identifying, analysing, and reporting patterns or themes within qualitative data. The email-based responses were carefully reviewed and translated, enabling the extraction of core themes such as digital self-service, customer engagement, operational automation, AI productivity tools, and data visualisation.

Thematic patterns were triangulated with industry whitepapers, internal materials, and academic literature, providing a multi-layered understanding of the company's digital transformation journey. This multi-source approach enhanced the credibility and robustness of the findings (Yin, 2018; Patton, 2015).

In addition to the written interviews, one of the participants voluntarily shared operational documents and dashboards that illustrated how data analytics are used in real-time decision-making. These visual examples enriched the analysis by demonstrating the integration of BDA tools into daily routines (Figure. 3 and Figure. 4).

All participants provided informed consent and approved the use of their responses for academic purposes. Due to internal confidentiality policies, both interviewees and the company requested anonymity. Accordingly, the company is referred to throughout this study as an “Iberian-based utility,” a designation that was agreed upon by the participants. All personal and institutional identifiers were anonymised in compliance with General Data Protection Regulation (GDPR) and ethical research standards (Bennett & Raab, 2020; Voigt & Von dem Bussche, 2017).

Chapter 3

3. Results

3.1 Context

The insights presented in this section are based on two distinct interviews, that conducted with professionals by two diverse teams directly involved in AI and BDA implementation within the Iberian-based utility. The perspectives offered focus primarily on digital customer interfaces, reflecting business-oriented and technical viewpoints. The analysis demonstrates how these technologies are being applied to strengthen digital self-service capabilities, automate internal workflows, and personalise customer engagement, while also highlighting the strategic use of BDA tools and digital platforms—such as "SmartFacilities"—for operational monitoring, anomaly detection, and data-driven decision-making.

3.1 AI as an Enabler of Personalised Energy Services

One of the primary objectives of the company's digital platforms—mobile apps, websites, and customer portals—is to empower customers to autonomously access information, submit requests, and manage their energy consumption in a convenient and secure manner. As stated by the Interviewee number 1 (I1), "*Around 60–70% of the company's servicing is already carried out through these channels*", confirming significant adoption of digital tools despite the current lack of customer-facing AI interaction.

This Digital Global Customer Channel employer identified two primary avenues for future development. First, the digitalisation of complex or low-volume use cases that are not yet covered by current systems. AI is viewed as a facilitator to automate and scale these services. For instance, "*we want customers to be able to interpret their energy bill with the help of AI*" (I1), which could enable the automatic extraction and explanation of charges, usage trends, and optimal household energy configurations.

The second area focuses on enhancing already digitised journeys. The current flows are often described as rigid, or rule based, "*improving the experience of already digitalised use cases by making them more fluid and intuitive, thereby increasing the adoption rate of digital channels and reducing reliance on assisted channels*" (I1), highlighting the strategic importance of moving customers away from costly channels like in-person service or call centres. This approach focuses on enhancing the usability of digital channels to incentivise customers to migrate from costly call centres and physical branches to self-service options applying AI to invoice interpretation, using machine learning and natural language processing to extract key consumption details, allowing customers to solve billing doubts without human intervention.

Nevertheless, technical barriers remain a challenge. The implementation of AI at the front-end requires robust support from the back-end systems, which was flagged as a key challenge: "*It's not enough to just have a digital interface with*

AI – core systems must also evolve accordingly" (I1). However, it was emphasised that customer interface improvements alone are insufficient. Any successful AI use case must be supported by robust core systems. Implementing AI in isolation, without back-end integration, results in disjointed service delivery. Internal system readiness thus remains a critical technical and organisational challenge which should be addressed and not forgotten.

3.2 AI for Enhanced Engagement and Automation

The company is actively exploring AI-powered chatbots and intelligent search bars for customer-facing portals. These tools are expected to reduce customer effort by providing fast, self-directed answers to common queries. As noted by one of the participants, *"AI tools are already used to support telephone operators [...] with considerable success, which gives confidence that something similar can be accessed directly by customers, in a reliable way, for a wide range of use cases"* (I1). These chatbots aim to handle inquiries in real-time, offering immediate and accurate responses, thereby reducing reliance on human agents. As noted, *"We are currently exploring various alternatives for implementing customer-facing AI chatbots to support our customer account areas"* (I1). In parallel, intelligent search functionality is being developed to improve information retrieval on the company's commercial websites, with the goal of *"as well as enhancing the capabilities of search bars using AI to improve customer access to information"* (I1). Internally, AI already supports call centre agents by retrieving information from a structured internal database since it was cited that *"(…) to support telephone operators by acting on the internal knowledge base or support library, with considerable success"* (I1). According to this participant, this success builds *"confidence that something similar can be directly accessed by customers, reliably, for a wide range of use* *cases"*. This reinforces the company's belief in the scalability and consistency of customer-facing AI service tools.

Another ongoing project involves the development of NBA and NBO models. These AI-driven recommendation systems are being designed to offer personalised energy advice: *"These AI models aim to establish an intelligent dialogue with the customer including comparisons with similar households, tariff recommendations, power adjustments, and optimal use of home energy equipment"* (I1). For example, customers may be advised to switch to a more suitable tariff, adjust contracted power, or invest in home energy solutions like solar panels or battery storage. These tools are meant to recommend optimised tariffs, compare user profiles with similar households, and suggest efficient usage of home energy assets like solar panels or heat pumps. This shift reflects a broader industry transition from passive utility service to active energy advisory. The company aspires to become a *"trusted partner that delivers relevant and actionable value propositions to each customer"* (I1), particularly in a context of rising complexity—dynamic tariffs, decentralised energy production, and evolving consumer preferences.

The pivotal aim of the Iberian-based Utility seems to be helping customers navigate an increasingly complex energy landscape characterised by volatile prices, new products, and higher frequency of interaction. By offering actionable, data-driven guidance, the company positions itself as a proactive and trusted energy advisor. As one participant explained, *"The energy world is shifting to a more dynamic, volatile and complex ecosystem […] customers won't want to be energy experts, so it's our role to act as an advisor and offer specific, personalised, data-driven value proposals"* (I1). AI's benefits are not limited to customer-facing operations since interviewees also highlighted the implementation of RPA for automating internal communications and alert systems at the Iberian-based utility reveals a pragmatic and results-driven approach to digital transformation. As stated in

Interview 1, "*our AI tools allow us to automate repetitive tasks such as automatic emails and alerts with Robotic Process Automation and the impact has been positive*" (I1) suggesting early-stage maturity and favourable outcomes in process simplification.

The adoption of AI-based coding assistants, or "co-pilots," was another emerging theme addresses in one of the interviews. These tools support development teams by automating code generation, unit test creation, and documentation. AI's role extends to supporting internal development teams, as stated, *"(..) several of our Dev teams are supported by co-pilots assisting in the generation of new code, unit test creation, or in documenting development processes"* (I1) enhancing productivity. Teams report reduced development time and a noticeable improvement in code quality and delivery speed. I1 also noted that while early results are promising, *"(..) early deployment stage, and it is certainly a journey of continuous improvement"* (I1), emphasising the need for ongoing refinement and upskilling to maximise value from these tools.

3.3 Leveraging BDA Tools for Operational Intelligence

The second interview revealed the significant role of digital platforms in optimising facilities management within the Iberian-based utility. The company initiated its digital transformation in this area around four years ago with the introduction of the *"SmartFacilities"* platform. As described by the interviewee number 2 (I2) from Data & Technical Management department, it *"(...) supports coworkers and customers assisting all individuals involved in asset and facility management in tracking their activities."* and"all the information recorded in the platform, such as response times or non-conformities identified during preventive maintenance or audits, is shared with us through Microsoft Azure services" (I2).

Despite these advantages, it was stated that *"we still don't have predictive maintenance systems implemented; we only work with preventive and corrective maintenance."* (I2) The main barrier to adopting predictive analytics lies in the difficulty of obtaining sufficient data volumes, especially as *"We depend, in part, on the data entered by service providers or, alternatively, we would need IoT systems on all equipment, which becomes very costly"* (I2). Although the company has not fully deployed predictive maintenance due to the prohibitive cost of equipping all assets with IoT, it has begun integrating targeted sensors (e.g., for air quality, temperature, and water usage) across select facilities. As I2 stated, *"This allows us to monitor (..) and identify any unusual water consumption."* These initial IoT deployments provide early indicators of infrastructure issues and demonstrate a foundational step toward more connected, data-driven operations. However, the lack of scale remains a major constraint, especially in a context where *"(…) we depend, in part, on the data entered by service providers or, alternatively, we would need IoT systems on all equipment, which becomes very costly."* (I2).

In terms of data-driven decision-making, the platform plays a key operational role. A central dashboard aggregates the most relevant operational data and is *"updated daily, preferably overnight, to ensure the data is as up to date as possible at the start of each workday."* (I2). The dashboard also monitors contractor performance and *"also reflect the service levels of the various providers and the ratings given by our customers. If service levels fall below what was contracted, penalties may apply"* (I2).

The platform's native reporting module is widely used for extracting specific operational insights: *"it's very useful when we need to quickly extract a specific list"* (I2). These reports complement the dashboards and allow the operational team to act faster and with greater precision. Real-time monitoring is also enabled through sensor integration: *"focused on the introduction of sensors for temperature, air quality, and water consumption"* (I2), which help flag anomalies instantly, also noted as: *"as soon as abnormal consumption is detected, the SmartFacilities platform receives a notification, allowing fast analysis and the identification of leaks preventing waste"* (I2). This proactive approach has already delivered tangible benefits in terms of efficiency and sustainability.

Automation is another key functionality of the platform. As explained, *"includes various automations, such as the automatic scheduling of interventions, creating interventions to resolve non-conformities, or initiating interventions to investigate suck as water leaks"* (I2). These features have improved the traceability and reliability of maintenance workflows and *"providing evidence during audits, making processes easier, thanks to structured reporting and traceable records"* (I1). It was also highlighted a pilot project currently underway, involving machine learning for managing building occupancy. *"(…) exploring models that allow us to understand the flow of people in and out of buildings"* (I2) although limitations remain due to GDPR compliance and privacy concerns. *"(…) We have encountered several barriers in this type of project, ranging from defining camera placement to managing stakeholder expectations"* (I2). Nonetheless, the initiative is regarded internally as *"a pioneering project that will go through several iterations."*

While *"SmartFacilities"* platform currently operating as a back-office system, the I2 confirmed its essential role in supporting customer-related services: *"it doesn't integrate directly with customer-facing platforms, but it's critical in responding to client and co-workers' requests and improving the experience in our physical spaces."* (I2)

Emphases on BDA tools—particularly dashboards through Power BI—play a fundamental role in operational monitoring and day-to-day decision-making within the Iberian-based utility. I2 explained that *"main dashboard that concentrates most of the operational information"*, updated daily to ensure accuracy and availability at the beginning of each workday. These dashboards consolidate critical service indicators, such as contractor response times and customer satisfaction scores, and are actively used to assess performance and enforce service-level agreements. *“If service levels fall below what was contracted, penalties may apply”* (I2), highlighting the strategic role of these visual tools. Beyond visualising performance, dashboards support a more proactive management style. For instance, “as soon as the system detects an abnormal water consumption, a task is automatically generated in the platform” (I2), which helps prevent further waste or potential damage. This interviewee addressed additional dashboard use cases currently in practice. One example involves monitoring the consumption of food and beverages in vending machines, allowing the company to optimise restocking efforts and avoid waste. It is updated every month by information sent from every facility manager, visible in the image below shared, via email, by the professional from the Data & Technical Management Department.

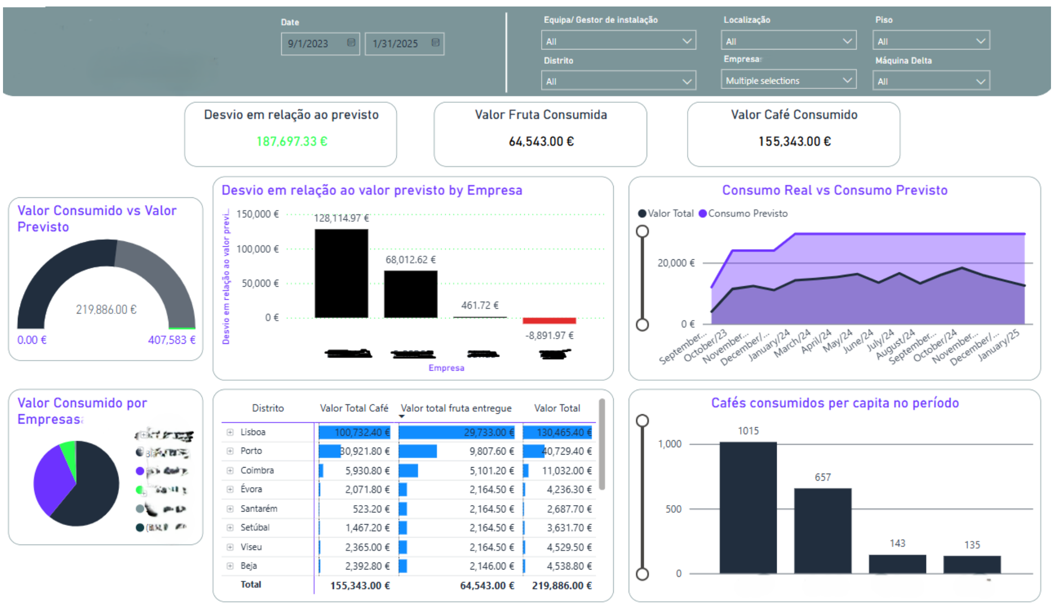

Figure 1. Food and Beverage Consumption Dashboard

Despite these advances, challenges persist. Integration with older systems remains a key limitation: *"dashboards are updated daily, preferably overnight, to ensure the data is as up to date as possible at the start of each workday"* (I2) reflecting the current lack of real-time data transfer capabilities. Moreover, ensuring the consistency and reliability of data across different systems is an ongoing concern, particularly given the diverse sources feeding the analytics infrastructure. These insights demonstrate that dashboards are well-established tools for operational visibility and strategic planning. However, their full potential is still hindered by infrastructure constraints and regulatory boundaries. As the utility continues its digital evolution, scaling these systems in real-time and improving interoperability will be essential for more responsive and efficient asset and facility management.

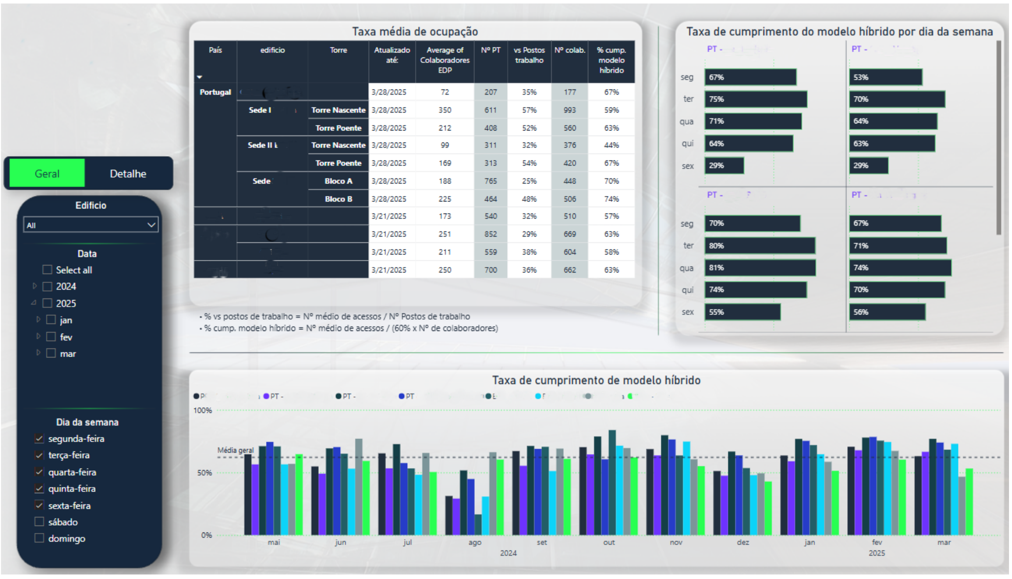

Figure 2. Occupational Rate of Buildings Dashboard

Although a dashboard on companies' occupancy rate was also revealed upon request, in the same email, illustrated above which provides a comprehensive visualisation of the company's occupancy rates and hybrid work model compliance across several international office locations. The central table highlights the average occupancy per building and tower, showing metrics such as the number of workstations), average accesses, and percentage of hybrid model compliance (in percentage). Overall, this dashboard supports I2 claims that monitoring tools such as Power BI dashboards are essential for tracking workplace dynamics, assessing real-time occupancy trends, and ensuring operational efficiency in hybrid work environments.

Furthermore, the second interview provided a deeper understanding of how Azure-based solutions and IoT sensors are enhancing facility management operations, generating tangible efficiencies through automation and data-driven responses. However, limitations such as the lack of predictive maintenance and the high cost of IoT deployment illustrate the gap between aspiration and full digital transformation.

The findings presented in a general perspective through both interviews reveal a clear and pragmatic use of AI and BDA tools within the Iberian-based utility, particularly in the domains of customer self-service, operational automation, and infrastructure management. From AI-supported co-pilots and chatbots under development to a specific platform that handles coworkers and customers' requests to automated dashboards that track building occupancy and vending machine usage, the utility demonstrates a progressive—though still evolving—digital maturity. These insights show that while strategic intentions and digital infrastructure are in place, challenges persist.

Overall, these results not only answer the research question on the practical use and barriers of AI and BDA in the energy sector and improving customer experience, but also highlight emerging opportunities for improved customer engagement, operational intelligence, and strategic agility. The following discussion section will critically examine these findings considering the existing literature, identifying alignments, gaps, and implications regarding these tools in the energy sector.

Chapter 4

4. Results Discussion

4.1 Context

This section critically discusses the results in relation to the research question: *"How can AI tools and BDA be used in the energy sector to improve OE?"* Drawing from two distinct themed interviews conducted with professionals from an Iberian-based utility and grounding the insights in the theoretical perspectives previously outlined, the discussion highlights how AI and BDA are applied across customer interfaces, asset management, and internal operations. The themes are structured according to the contextual drivers, challenges, interventions, and outcomes identified.

4.2 AI as Driver of Strategic Digital Transformation

The findings reveal that AI and BDA have been integrated as strategic enablers across the utility's digital infrastructure. As Mikalef et al. (2020) and Gandomi and Haider (2015) suggest, such technologies are critical in enabling agility and responsiveness in data-rich, service-oriented industries like energy.

The empirical findings from both interviews not only affirm the theoretical frameworks discussed in the literature but also reveal practical nuances specific to the energy sector's digital transformation journey. For example, the utility's emphasis on customer autonomy through digital channels supports the claims of Haenlein et al. (2022) and Huang and Rust (2021), who argue that AI-driven personalisation and self-service are critical in enhancing customer experience with the company's strategic use of apps and portals—handling 60–70% of servicing—demonstrates the operationalisation of this theory in a real-world energy context.

Moreover, the interviewee's description of AI-powered chatbots and intelligent search tools under development directly aligns with Adam et al. (2021) and Xu et al. (2021), who highlight the scalability and efficiency of such technologies in customer service. The transitional strategy of first supporting internal agents through AI tools before expanding to fully autonomous chatbots exemplifies a phased, trust-building implementation approach echoed in the literature.

The development of NBA and NBO models resonates with Huang et al. (2021) and Chatterjee et al. (2021), who stress the value of predictive analytics in customer engagement. The Iberian-based utility's ambition to become an energy advisor, delivering personalised, data-driven insights, confirms the broader sectoral shift toward proactive customer value delivery.

This maturity is accompanied by efforts to enhance the digital experience through AI tools, such as chatbots and NLP-powered search functions. These developments align with Adam et al. (2021), who note the growing role of chatbots in reducing operational costs and improving user responsiveness. The company's exploration of AI for automating invoice interpretation further demonstrates the utility of AI in managing unstructured data—a capability emphasised by Gandomi and Haider (2015).

RPA and AI-based coding assistants ("co-pilots") are being used internally to streamline back-office and IT workflows. These tools automate tasks like customer data updates, code generation, and documentation. Processes such as customer account updates, invoice handling, and data entry can be largely automated, resulting in faster execution, fewer errors and therefore better efficiency. The interviewees also stressed that AI adoption requires constant refinement, echoing the organisational learning curve described by Brock and von Wangenheim (2019). For those reasons, the Iberian Utility mentioned the use of chatbots previously in their operations although their website does not provide a virtual assistant anymore and are evaluating an improved implementation path. This testimony corroborates existing literature that recognises RPA as a foundational layer of digital transformation within energy companies. It supports earlier findings by Lacity and Willcocks (2021), who emphasise RPA's ability to free human capital for higher-value tasks by automating rule-based operations. In the Iberian-based utility, the deployment of RPA demonstrates clear alignment with these strategic goals, targeting repetitive communications and task execution to improve process speed and accuracy. The interview insight not only validates theoretical expectations but also reveals a positive organisational perception toward AI-enabled automation tools — a key factor for scaling digital initiatives. The interviewee's comments on automating billing, data entry, and development workflows offer direct, practical examples of how AI and automation are streamlining operations and freeing resources for higher-value tasks where AI's effectiveness can be maximised when accompanied by agile methodologies and continuous training, both of which were acknowledged by participants as key to the success of co-pilot tools and automation platforms (Haenlein et al., 2022).

4.3 BDA Tools in Operational and Strategic Decision-Making

Visual analytics tools such as dashboards are becoming central to decision-making processes in energy utilities. By consolidating key performance indicators (KPIs), service level agreement (SLA), and resource consumption data, dashboards offer managers and technicians a transparent view of operations. Knight and Page (2020) suggest that dashboards enhance real-time responsiveness, allowing organisations to detect anomalies—such as excessive resource use—and intervene promptly supported by platforms like Power BI. Frolov et al (2021) is linked with dashboards connected to IoT devices can extend their value by providing predictive alerts and supporting maintenance planning. These tools not only facilitate operational control but also contribute to behavioural insights, enabling utilities to optimise vending machine stocking, track building occupancy, and support sustainability goals through data-driven facility management.

However, integration with legacy systems remains a challenge, consistent with findings from Zhou et al. (2016), who highlight that outdated IT infrastructures often hinder the real-time application of BDA. This was evident in the interviews, where daily dashboard updates were updated at night, reflecting a lack of live integration since dashboard are used for strategic decision-making. The second interview's discussion around *"SmartFacilities"* and Azure integration further substantiates Frolov t al (2021), who emphasise the importance of integrated platforms for asset management. This system's real-time dashboards and automated interventions, such as water leak detection and occupancy tracking, demonstrate how BDA tools are embedded in facility operations—a key element in enabling predictive, data-driven decisions.

Yet some challenges need to be addressed—such as the cost of IoT infrastructure, limitations of legacy systems, and compliance constraints under GDPR—reaffirm concerns raised in the literature by Gandomi and Haider (2015), and Brock & von Wangenheim (2019) regarding technical debt, data governance, and organisational readiness. The utility's iterative approach to deployment, using pilots and progressive integration, exemplifies the type of adaptive strategy recommended by Creswell and Poth (2018) in navigating complex digital transformations.

4.4 Final Discussions

The results collectively confirm that AI and BDA are indispensable to both customer-centric and operational transformation. As Kumar et al. (2021) argue, smart analytics are foundational to managing decentralised grids and engaging informed energy consumers. The Iberian-based utility's strategy—phased deployment, back-end integration, and cross-functional coordination—reflects a model of controlled innovation, which the literature suggests is crucial for scalability (Wamba et al., 2020; Creswell & Poth, 2018).

In summary, the insights derived from the interviews with professionals at the Iberian-based utility validate and deepen the existing literature on the adoption of AI and BDA in the energy sector. By situating these technologies within concrete operational and customer-facing contexts, the findings illustrate that AI and BDA are not merely conceptual frameworks, but active enablers of operational efficiency and digital transformation. They support automation, streamline decision-making, and enhance responsiveness—particularly through tools such as predictive analytics, Robotic Process Automation (RPA), and AI-powered co-pilots. Nevertheless, the analysis also underscores that the successful implementation of these tools depends on addressing persistent organisational and technical challenges, including the integration of legacy systems, data reliability, and compliance with regulatory frameworks. These considerations are essential for unlocking the full potential of AI and BDA in future-proofing energy operations.

These results confirm that while the company is progressing towards a data-driven, customer-centric model, the scalability and long-term value of these technologies will depend on continued investment in systems interoperability, workforce upskilling, and strategic governance. Thus, the Iberian-based utility represents a compelling case of evolving digital maturity, providing relevant lessons for the broader energy sector navigating similar transitions.

Chapter 5

5. Conclusion

5.1 Context

The Iberian-based utility explored in this research presents a compelling case of a company navigating the transition from digital experimentation to strategic integration. While challenges persist—including legacy system constraints, skill gaps, and regulatory hurdles—the trajectory is clear: AI and BDA are becoming indispensable pillars of modern utility operations.

By delivering real-time insights, automating workflows, and reshaping customer journeys, these technologies are helping energy providers align operational performance with customer expectations in a fast-changing market. As the sector continues to evolve, those who invest early in intelligent, interoperable, and customer-oriented AI and BDA strategies will be better positioned to lead the next wave of sustainable, data-driven energy innovation.

5.2 AI and BDA as Strategy Enablers

From an applied perspective, the Iberian-based utility also demonstrates how AI and BDA can be integrated into both customer-facing and operational layers. As I1 described ongoing pilots for customer-facing chatbots, supported by backend AI already used in call centres, which reinforces the internal validation-before-scaling approach. As so the implementation of NBA and NBO models can reflects a strategic move toward real-time, data-driven customer advising. For example, AI-generated energy-saving recommendations and tariff comparisons position the utility as a proactive partner in the customer's energy journey by analysing house capacities and consumer billing and would allow them to differentiate from the competition.

Moving forward, it is recommended that the utility formalise an automation roadmap that identifies further high-volume, rule-based processes suitable for RPA. This strategy should be integrated with continuous monitoring frameworks to track ROI, user adoption, and productivity gains, thereby ensuring the long-term sustainability and scalability of automation efforts.

The I2 highlighted significant limitations in the utility's ability to scale predictive maintenance due to the high costs and data infrastructure demands associated with IoT deployments. Future research could explore how different energy companies prioritise IoT integration across diverse asset types, and how modular or hybrid sensor strategies could be optimised for cost-effectiveness. This research may benefit from quantitative case studies assessing ROI and operational risk reduction from selective IoT use, especially in geographically distributed infrastructure.

The I2 noted the platform's ability to issue automated alerts in response to abnormal water consumption, which helps in the early detection of leaks. Future research should assess the effectiveness and responsiveness of these alert mechanisms by studying the time-to-intervention, cost of delayed detection, and environmental impact (e.g., water savings) associated with such systems. Researchers could also explore user trust in alert systems and how often they trigger false positives or unnecessary interventions.

The use of dashboards to track contractor performance, customer satisfaction, and SLA compliance emerged as a powerful managerial tool. The Iberian Utility could delve into how dashboard-driven decision-making shapes vendor relationships, accountability, and operational transparency. For example, comparative studies could analyse how the granularity and frequency of dashboard updates and penalties affect service responsiveness and contract renegotiation practices. Future research should explore the human-centric dimensions of AI and BDA adoption in the energy sector.

Finally, the company can be encouraged to investigate the cost–benefit dynamics of AI and IoT investments in operational infrastructures. For instance, future studies could quantify the ROI of IoT-enabled predictive maintenance versus traditional preventive maintenance across different scales of energy infrastructure. Such economic analyses would be instrumental in supporting data-driven decision-making for utilities facing budgetary constraints and competing priorities.

5.3 Practical Recommendations and Suggestions

The second interview revealed that the Iberian-based utility has yet to implement predictive maintenance at scale, primarily due to the significant financial and technical burdens associated with equipping geographically dispersed facilities with IoT sensors. A promising direction for future development involves the adoption of tiered or prioritised IoT deployment strategies. Rather than aiming for universal sensor coverage, companies could begin by identifying high-risk or mission-critical assets—such as HVAC systems, water infrastructure, or energy-intensive equipment—based on failure frequency, replacement cost, or operational criticality. This phased rollout should be accompanied by cost-benefit analyses comparing facilities with full, partial, and no IoT integration, assessing improvements in fault detection accuracy, maintenance lead times, and energy efficiency gains.

The SmartFacilities system, as described in Interview 2, currently delivers daily updated dashboards that monitor operational variables, contractor performance, and SLA compliance. While these dashboards already inform day-to-day decision-making, their full strategic value could be expanded. Future implementations should assess how real-time analytics enhance responsiveness by tracking KPIs such as mean time to repair (MTTR), reduction in service disruptions, and improved coordination with external service providers. Additionally, dashboards should evolve from passive monitoring tools into interactive decision-support systems, integrating predictive alerts and optimisation algorithms.

Systemic challenges were repeatedly raised in both interviews, notably the rigidity of legacy IT systems, the absence of real-time integration, the high costs associated with digital infrastructure, and the cultural resistance to automation and AI. These barriers continue to limit the scalability of AI and BDA across both customer-facing and operational domains. To address these, utilities must invest in backend modernisation, ensuring that core systems are interoperable with newer AI modules and capable of supporting dynamic, data-driven services. This may involve the creation of secure, real-time data pipelines, as well as the gradual replacement or refactoring of outdated platforms.

Furthermore, any long-term digital strategy must be anchored in a comprehensive AI governance framework, ensuring that the adoption and scaling of AI and BDA tools are not only technologically sound but also ethically responsible, legally compliant, and socially sustainable. This becomes especially important in highly regulated sectors such as energy, where data sensitivity, transparency, and public trust are paramount.

The framework should establish clear protocols for data ethics, transparency, and accountability. This includes defining ownership and access rights for data collected through AI and IoT systems, particularly when customer data, operational metrics, or third-party contractor information is involved. Transparent logging of AI decisions, particularly in customer-facing tools such as chatbots or recommendation engines, should be standard practice to ensure explainability and trust.

Full alignment with data protection legislation, such as the General Data Protection Regulation (GDPR), is non-negotiable. As Interview 2 highlighted, current constraints in AI-based building occupancy monitoring stem from legal limitations—such as restrictions on identifying individuals through video analytics. Therefore, the governance model must proactively integrate privacy-by-design principles and embed risk assessments for new AI initiatives. Practical steps include conducting Data Protection Impact Assessments (DPIAs) prior to deployment and implementing automated anonymisation techniques where necessary.

The Iberian Based Utility should promote human-centred AI design, ensuring that AI systems are built to support, not replace, human decision-makers. This is particularly relevant for internal applications like co-pilots or dashboards, where AI augments the work of developers, facility managers, and call centre operators. In practice, this means creating feedback loops between human users and AI systems, where employees can refine, override, or report AI decisions that are perceived as inaccurate or misaligned with operational objectives.

The interviews demonstrated that while co-pilots and other AI tools are already in use, the full benefits remain contingent on workforce readiness. Therefore, utilities should implement structured training programmes tailored to different departments—ranging from basic AI literacy for non-technical staff, to advanced analytics and model governance for data teams. Cross-functional learning groups or internal "AI communities of practice" can also facilitate knowledge sharing and innovation diffusion across silos.

5.4 Final Conclusions

This journey concludes with the sense that its true point of departure may only now be fully understood—had greater foresight and analytical clarity been available from the outset. What this research has sought to achieve is a synthesis of evolving practices and strategic insights, shaped by the dynamic and multifaceted nature of technological transformation in the energy sector. At its core, the thesis aimed to spark discussion on how AI and BDA are being embedded into organisational routines—not as static solutions, but as adaptive, ever-advancing systems. Their continuous evolution demands ongoing reflection, agility, and critical engagement, ensuring that digital innovation remains aligned with the complex realities of customer experience, operational efficiency, and strategic foresight.

Expanding upon the insights generated in this study, future research should adopt broader and more diverse methodological frameworks to validate and deepen the conclusions presented. Conducting multi-case studies across energy providers operating in different geographic, regulatory, and technological contexts would provide a more nuanced understanding of how AI and BDA adoption unfolds across the sector. Such comparative analyses could reveal structural, cultural, or market-based factors that either facilitate or hinder successful digital transformation.

A mixed-methods approach—combining qualitative interviews with quantitative performance indicators such as customer satisfaction levels, service adoption rates, and operational cost reductions—would strengthen the evidence base and enable more robust conclusions. Furthermore, given the increasingly customer-centric nature of AI applications, future studies should investigate end-user perceptions of AI tools like chatbots, recommendation systems, and digital assistants. Understanding user trust, comfort, and expectations is essential to evaluating the real impact of personalisation and automation on consumer engagement and loyalty.

It is also imperative that future inquiry addresses the economic and technological scalability of predictive maintenance models, particularly in environments with geographically dispersed and complex infrastructure. This includes assessing ROI of IoT integration and evaluating its feasibility in different operational scenarios as AI and BDA tools become more embedded in decision-making processes, research should critically engage with their ethical and social implications. This includes examining how energy companies balance innovation with regulatory compliance, data transparency, and algorithmic fairness—especially in customer-facing contexts where data sensitivity is high.

In conclusion, this thesis has demonstrated how AI and BDA are being strategically and operationally applied within an Iberian-based utility to enhance customer experience and internal efficiency. Through an in-depth case study grounded in empirical interviews, the study has shown that these technologies not only serve as enablers of digital self-service and operational automation but also play a central role in shaping more personalised, responsive, and sustainable energy services. While tangible benefits are evident, the transition to fully intelligent and integrated systems is still maturing—hindered by technical, organisational, and regulatory constraints. Nevertheless, the findings provide a practical roadmap and a theoretical foundation upon which both practitioners and scholars can build. Continued investigation into these tools, their adoption pathways, and their broader implications will be critical as the energy sector seeks to navigate the complex demands of digital transformation, consumer empowerment, and sustainable innovation.

Prompts List section

1. "Help me integrate this interview insight about RPA with academic literature on automation in the energy sector."
2. "Suggest academic references to support the link between predictive maintenance and operational efficiency."
3. "Refine this paragraph for clarity, academic tone, and correct grammar."

During the preparation of my written work/thesis, “The case study of an Iberian Based Utility”, ChatGPT was used for the following tasks: integration of interview insights with literature, and citation support, with the prompts used listed at the end of the document in the Prompts List section. After using this(these) tool(s)/service(s), I reviewed and edited the content as necessary, 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.

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Appendices

Appendix 1 – Interview Script 1

1. How is your company currently applying AI to enhance digital customer self-service, and what are the next steps in this journey?

2. What AI-based tools are currently being explored or implemented to improve customer self-service and support in your digital channels?

3. How is your company using AI to provide personalized energy advice to customers?

4. In what ways is AI being leveraged internally to enhance the productivity?

Appendix 2 – Interview Script 2

1. Does your company currently use any tools to support asset and facilities management? If so, what are the main data these tools collect and how are they analysed? Do you use Big Data Analytics techniques to identify patterns or anticipate maintenance needs?

2. What kinds of dashboards or reports does the platform generate, and how are they used to support decision-making or improve operations and customer service?

3. Does this tool collect and analyse real-time data? If yes, what types of indicators are monitored and how are they used to improve operational efficiency?

4. Is there any system or Big Data Analytics tool or predictive algorithm applied to this platform to anticipate maintenance needs or optimise asset management? Can you elaborate?

5. Does the platform support automated scheduling or task prioritisation? Are BDA techniques used to detect patterns or anticipate maintenance needs?

6. Is the Iberian Utility currently developing any innovative project using AI tools, dashboards, or advanced operational control analytics? Can you share any example or ongoing initiative and its difficulties?

7. Is there any integration between this tool and the company's other digital platforms, such as apps or customer portals? If so, are the insights from asset management reflected in the digital customer experience (e.g., alerts, consumption forecasts, outages)?

Appendix 3 – Interviews Scheme

Theme Area	Guiding Question	Interviewee 1 (Digital Customer Channels)	Interviewee 2 (Technical & Facilities Management)
Use of AI/BDA	What AI or BDA techniques/tools are being used?	NLP, NBA/NBO, RPA, co-pilots	Power BI, IoT-based dashboards, anomaly detection

Tools and Platforms	Which platforms or tools are used to support AI/BDA deployment?	Internal portals, chatbots (under development), co-pilot, search bar with AI	SmartFacilities (Nextbitt), Azure, IoT sensors
Analytical Approaches	What types of analytics are applied?	Personalisation engines, customer profiling, support automation	Descriptive and anomaly-based analytics
Organizational Culture	Where are analytical skills located within the company?	Spread across digital, CRM, marketing, and development teams	Concentrated in facilities/data teams
	Is there a data-driven culture within the organisation?	Strong at leadership level, progressively expanding	Encouraged but limited by stakeholder maturity
	What supports this culture?	Leadership vision, digital transformation roadmaps	Leadership encouragement, investments in dashboards
	What hinders this culture?	Legacy systems, resistance to change	Limited technical skills, unclear expectations
Operational Usage	How are AI/BDA insights used in operations or decision-making?	Decision support for service personalisation, support automation	Maintenance scheduling, anomaly detection
	What types of reports/dashboards are generated?	AI metrics for channel use, digital interaction patterns	Daily dashboards for SLAs, vendor performance, alerts
	Do these dashboards influence real decisions?	Under development, some evidence of positive impact	Yes – tied to KPIs, contract enforcement, real-time alerts

Benefits & Barriers	What are the key benefits observed?	Reduction in call centre volume, personalised service, process automation	Increased monitoring capability, quicker decision-making
	What are the main barriers?	Integration with legacy systems, GDPR concerns, skill gaps	High IoT costs, limited predictive capabilities, dependence on vendor data
Future Suggestions	What would improve the effectiveness of AI/BDA implementation?	Aligning front-end AI with core systems, investing in user-friendly automation	Expanding sensor coverage, refining dashboards and implement predictive modelling pilots

Table 2. Interview Insights

Appendix 4 - Interview Summary Table

Both interview transcripts are available on the link below:

- Interviews_Transcript