UNIVERSIDADE CATÓLICA PORTUGUESA

Challenges to the Implementation of AI in Organizations

An Empirical Analysis of Implementation Drivers and Challenges

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Católica Porto Business School
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Abstract

Artificial Intelligence is no longer a futuristic vision. It is transforming how organizations operate, compete, and innovate. Yet, while its potential is widely recognized, implementation remains complex and uncertain. This study explores the drivers, benefits, barriers, and strategic tensions of AI adoption across four dimensions: organizational, social, technological, and financial.

Using a qualitative, exploratory approach, the research combines a literature review with insights from 20 semi-structured interviews with professionals across diverse sectors. Findings show that leadership support, change management, and workforce reskilling are essential to successful implementation. Social factors, including expectation management and fears of job displacement, also play a key role. Technological readiness, particularly data infrastructure and regulatory compliance, emerges as both an enabler and a constraint. Financial considerations are relevant but less decisive than the ability to demonstrate strategic value and long-term returns.

The study also finds that organizations often struggle to measure AI's true impact. While most rely on informal feedback, early evidence points to clear gains in productivity, cost savings, and customer experience. By connecting academic insight with real-world practice, this research offers not just analysis but a roadmap for organizations seeking to turn AI from a buzzword into a competitive advantage.

Keywords: Artificial Intelligence, AI Adoption, Organizational Change, Technological Readiness, Workforce Reskilling, Data Infrastructure, AI Regulation

Resumo

A Inteligência Artificial deixou de ser uma visão futurista. Está a transformar a forma como as organizações operam, competem e inovam. No entanto, apesar do seu potencial amplamente reconhecido, a sua implementação continua complexa e incerta. Este estudo analisa os principais fatores de impulso, benefícios, barreiras e tensões estratégicas na adoção de IA, com base em quatro dimensões: organizacional, social, tecnológica e financeira.

Com uma abordagem qualitativa e exploratória, a investigação combina uma revisão crítica da literatura com insights de 20 entrevistas semiestruturadas com profissionais de diversos setores. Os resultados indicam que o apoio da liderança, a gestão da mudança e a requalificação da força de trabalho são cruciais para o sucesso da implementação. Fatores sociais, como a gestão de expectativas e o receio de substituição de empregos, também se destacam. A preparação tecnológica, especialmente a infraestrutura de dados e a conformidade regulatória, surge como facilitadora e barreira. Questões financeiras são relevantes, mas menos determinantes do que a capacidade de demonstrar valor estratégico e retorno a longo prazo.

O estudo conclui que as organizações enfrentam dificuldades em medir o impacto real da IA. Embora muitas dependam de feedback informal, os primeiros sinais apontam para ganhos em produtividade, redução de custos e experiência do cliente. Ao unir teoria e prática, esta investigação oferece não apenas uma análise, mas um roteiro para uma adoção eficaz e sustentável da IA.

Palavras-chave: Inteligência Artificial (IA); adoção de IA; mudança organizacional; prontidão tecnológica, requalificação da força de trabalho, infraestrutura de dados, regulação da IA

Abbreviations

AI: Artificial Intelligence

BCG: Boston Consulting Group

EU: European Union

GDPR: General Data Protection Regulation (also referred to as RGPD in Portuguese contexts)

IT: Information Technology

LLM: Large Language Model

MIT: Massachusetts Institute of Technology

NPS: Net Promoter Score

PoC(s): Proof of Concept(s)

R&D: Research & Development

ROI: Return on Investment

SME(s): Small and Medium Enterprises

Contents

Table of Figures

Table of Tables

Chapter 1
Introduction

1.1 Background and Motivation

Artificial Intelligence (AI) has evolved from a conceptual innovation into a practical, disruptive force reshaping modern business environments. Once confined to experimental laboratories and specialized industries, AI technologies are now integral to mainstream organizational operations, offering unprecedented opportunities for efficiency gains, market differentiation, and strategic transformation (Jan et al., 2023). However, as AI becomes more pervasive, so too do the challenges surrounding its adoption and integration into organizational structures.

According to the World Economic Forum (2025), AI is expected to create over 11 million jobs while displacing 9 million others by 2025. This reflects the dual nature of AI's impact, generating both opportunities and risks. As a result, organizations face mounting pressure to understand and manage the multifaceted dynamics of AI implementation.

1.2 Purpose and Objectives of the Study

The purpose of this study is to explore the factors that enable or hinder the implementation of Artificial Intelligence in organizational settings. Specifically, it focuses on four interrelated dimensions: organizational, social, technological, and financial. By examining these dimensions, the aim is not only to understand the factors that facilitate or obstruct AI adoption but also to derive actionable insights for enterprises navigating this evolving landscape. while contributing to the growing body of knowledge on digital transformation.

1.3 Research Question

The literature review revealed that AI implementation in organizations is shaped by a combination of organizational, social, technological, and financial factors. While its benefits are widely acknowledged, significant barriers persist across these dimensions. To explore this complexity, the study is guided by two main research questions:

RQ1: What are the main drivers and benefits that encourage organizations to implement AI across organizational, social, technological, and financial dimensions?

RQ2: What are the primary barriers and challenges that hinder the implementation of AI in organizations across the same dimensions?

These questions aim to support a comprehensive understanding of the opportunities and constraints organizations face when adopting AI.

1.4 Structure of the Study

This study is structured in a way that reflects a logical and progressive research process.

The second chapter presents a critical literature review that synthesizes existing academic work on AI adoption and implementation, organizing it around the four core dimensions mentioned above. This theoretical foundation helps clarify which factors have been identified as facilitators or obstacles to AI integration.

Following the literature review, the third chapter outlines the research methodology. It details the qualitative, exploratory approach employed, specifically the rationale for selecting semi-structured interviews, the criteria for participant selection, and the procedures for data collection, transcription, translation, and thematic analysis.

The fourth chapter presents the findings derived from the interviews, providing a systematic overview of participants' perspectives on the benefits and challenges of AI adoption. The findings highlight organizational factors, such as leadership commitment and employee training, as predominant influencers, followed by insights into the social implications, technological challenges, and financial considerations.

The fifth chapter interprets these findings in light of the reviewed literature, identifying areas of alignment and divergence. Particular attention is paid to emerging concerns such as the evolution of organizational culture, the role of expectation management, and the importance of data governance and regulatory compliance.

Finally, the sixth chapter offers the conclusion of the study. It summarizes the key findings, outlines the contributions of the study to both academic research and managerial practice, acknowledges the study's limitations, and proposes directions for future research.

By combining theoretical frameworks with empirical insights from industry practitioners, this research aspires to deepen the understanding of AI implementation and support organizations in making more informed, strategic decisions in this evolving technological landscape.

Chapter 2
Literature review

This chapter aims to critically cover and analyze the existing literature related to the topic of AI implementation in enterprises, and the understanding of the benefits and barriers in the way of successful adoption.

The literature review explores the tension between the drivers and enablers of AI adoption and the barriers and limitations that hinder its successful implementation. It then narrows its scope to four dimensions: organizational, social, technological, and financial, each shedding light on what enables or constrains successful AI integration.

The evolution of AI in recent years has transformed it from a niche theoretical concept into a practical, widely adopted technology across various sectors. Once limited to specialized domains, AI now permeates mainstream business activities and operations (Jan et al., 2023).

According to the World Economic Forum, AI is predicted to be the most disruptive technology trend, expected to create more than 11 million jobs, while simultaneously displacing 9 million others. (The-Future-of-Jobs-Report-2025, 2025).

Given this dynamic environment, this study seeks to investigate the drivers that encourage organizations to implement AI and the barriers that impede such efforts. The ultimate aim is to comprehend the complexities surrounding AI adoption and to identify actionable insights that can inform more effective implementation strategies.

2.1 Drivers and Barriers to AI Implementation

A growing body of literature has examined the enablers and inhibitors of AI adoption in organizations. On one hand, AI presents opportunities to enhance operational efficiency, improve strategic decision-making, and foster innovation across industries (Kaggwa et al., 2024).

On the other hand, the implementation of AI systems poses significant challenges for organizations as the scope and depth of potential applications increase and the use of AI becomes more mainstream (Dwivedi et al., 2021).

These dynamics have led researchers to categorize the key drivers and barriers into several domains, including social, technological, organizational, economic, political, legal, human, and ethical factors (Dwivedi et al., 2021; Shahzadi et al., 2024).

The present study narrows its focus to four specific categories: organizational, social, technological, and financial, which are particularly relevant for enterprise settings. Each is examined in the sections that follow.

2.1.1 Organizational Factors

Organizational culture has emerged as a pivotal determinant of AI adoption. Defined as the shared beliefs, norms, and values that characterize an organization (Merhi et al., 2024), culture shapes interactions, collaboration, and openness to innovation

It is a multilayered, complex concept that comprises a variety of aspects, such as the behavior of superiors, which influences the leadership culture, and the composition of teams, which shapes the culture of communication and cooperation. All these factors are connected by an 'invisible glue' – the organizational culture that permeates the organization (Korherr et al., 2023).

To support AI integration, a level of corporate culture transformation is required. Changes in mindset of both leaders and employees can be quite

challenging, and to get over the hurdle, companies must invest in training and development programs to equip their workforce with the right set of skills to effectively leverage AI. It is crucial to foster a culture of continuous improvement through learning and innovation, where people are encouraged to explore new technologies and apply them in their work (Kaggwa et al., 2024).

Managers and executives have the responsibility to define the vision, mission, values, and culture of the organization, making them a determinant of the success of the implementation process of the studied technology. When aligned with the right set of priorities, resources, and sponsorship, managers can be pivotal enablers for AI by influencing employees' trust in it, reducing resistance to change, and fostering curiosity (Merhi et al., 2024) .

2.1.1.1 Metrics and Impact Measurement

Measuring the impact of the implementation of AI in an organization is not always as straightforward as one might think; however, it is crucial to understand what has changed and how it has changed in order to evaluate performance and the return on investment on the adoption of this technology. As Mr. Wonderful (Kevin O'Leary) once said: "If you can't measure it, you can't improve it." A joint report by MIT and BCG identifies several metrics relevant to evaluating AI's organizational impact, including gains in efficiency, competitive advantage and market expansion, reduction of operational costs, and boring current tasks, increased precision, and lastly, time cuts in R&D time (Ransbotham et al., 2017). Yet, overreliance on quantitative measures may obscure key qualitative factors, such as the need to understand employees' AI perception and how it influences engagement and user adoption, to evaluate the success of the tool's adoption process (Dwivedi et al., 2021). A nuanced framework should combine both, allowing organizations to assess ROI while adapting to contextual factors.

2.1.2 Social Factors

Social dynamics also influence the successful implementation of AI. According to (Sun et al., 2019) unrealistic public expectations and insufficient awareness of AI's benefits can inhibit its broader adoption. Additionally, the ongoing transformation of the workforce raises critical concerns.

The McKinsey "*A new future of work*" report highlights the executives' worries about the changing work landscape, as mentioned, the lack of skills, and skills mismatch are factors to consider when considering leveraging the value from AI. It's worrying managers that by 2030, the workforce still won't have the right skills to deal with the technology and cause harm to the company's financial performance. (Hazan et al., 2024) suggest three strategies to address this: upskilling existing employees, hiring new talent, or outsourcing. Each entails trade-offs—while retraining supports cultural continuity and boosts morale, external hires may address immediate needs but introduce integration risks and cultural misalignment, adding an element of unpredictability.

Though displacement is real, AI is also expected to create new jobs. Navigating this trade-off requires thoughtful workforce planning and communication strategies to build trust and engagement.

2.1.3 Technological Factors

Although AI is becoming increasingly prevalent, many organizations remain unprepared for its adoption.

(Mikalef et al., 2019) stress the importance of big data analytics capabilities in enabling data-driven decision-making, while (Korherr et al., 2023) highlight the need for high-quality data and robust IT infrastructure. It is increasingly important to have the capacity to store and process huge amounts of data to improve operational insights generation, identify inefficiencies and bottlenecks,

detect changes in the complex economic and business environment, and monitor changes in the competitive landscape in real-time.

AI systems depend fundamentally on data (Thierer et al., 2017), and as such, the accuracy, reliability, and availability of data are pivotal. Poor data quality undermines outcomes and confidence in AI solutions (Merhi et al., 2024).

Furthermore, outdated data ingestion protocols and fragmented data structures create integration challenges. Achieving interoperability, such as a "single source of truth" that accurately reflects the operational reality, requires standardized data architectures and interdepartmental collaboration to overcome organizational silos (Dwivedi et al., 2021; Korherr et al., 2023). This reinforces that technological challenges are also organizational in nature.

As (Merhi et al., 2024) states, a well-established IT infrastructure is crucial and a prerequisite to AI adoption, comprising tangible and intangible resources, AI will always need components such as servers, storage and hardware allied with the knowledge and human resources to manage and extract the most out of the tool's implementation.

Lastly, Generative AI, including large language models, has recently emerged as a transformative force in business environments. It enables new applications such as natural language generation, automated coding, and customer service support. However, it brings new concerns such as hallucination, ethical use, and data bias (Fosso Wamba et al., 2024; Peres et al., 2023).

2.1.3.1 Data Privacy and Security

Data is the base of the pyramid concerning AI implementation. Privacy and security of data in its collection and processing stages were identified by (Fosso Wamba et al., 2024) as major challenges for organizations. High-profile incidents have pushed institutions like JPMorgan to restrict the use of large language models (LLMs) due to fears of accidental data leaks (Wong, 2024).

In healthcare, strict regulation is essential to maintain trust.

In healthcare, where AI is applied to highly sensitive data, similar concerns prevail. (Hee Lee et al., 2021; Murdoch, 2021) emphasize the importance of adhering to stringent regulatory frameworks to safeguard patient data and uphold ethical standards. Implementing robust measures, such as consent management and access control policies, is crucial to prevent unauthorized access to sensitive personal information.

The European Union's AI Act (2024) further codifies responsibilities by categorizing systems based on risk, thereby increasing scrutiny of high-risk applications. This regulation places additional compliance requirements on high-risk AI systems and restricts certain practices deemed unacceptable, thus influencing AI strategies in sectors such as healthcare, finance, and public services (Office of the European Union L- & Luxembourg, 2024).

2.1.4 Financial Factors

AI implementation entails substantial financial investment. Building and maintaining the necessary data infrastructure, acquiring advanced AI technologies, and attracting or upskilling talent all demand substantial resources to meet the high-performance demands of AI systems. For small and medium-sized enterprises, these costs can be especially prohibitive (Shahzadi et al., 2024).

Moreover, the return on investment may not be immediate. Competitive pressures often push companies to seek short-term results, yet the benefits of AI typically unfold over time, as systems mature and are fully integrated into decision-making processes (Kamoonpuri et al., 2023). Consequently, organizations must weigh the long-term strategic value of AI against the initial financial burden.

2.2 Formulation of the research questions

Overall, this literature review provides a comprehensive overview of the implementation of AI in enterprises. It is a multifaceted process shaped by organizational culture, societal readiness, technological infrastructure, and financial constraints. While its benefits are vast, significant hurdles remain. A nuanced understanding of these dimensions is essential for developing strategies that foster successful adoption. This chapter has laid the groundwork for subsequent empirical analysis by identifying the key factors that influence AI implementation in organizational settings.

In line with what was mentioned in the Introduction, two research questions (RQ) stem from the literature review:

RQ1: What are the main drivers and benefits that encourage organizations to implement AI across organizational, social, technological and financial dimensions?

RQ2: What are the primary barriers and challenges that hinder the implementation of AI in organizations across the same dimensions?

Chapter 3
Methodology

This chapter outlines the methodological approach used to answer the research questions and describes the context in which the project was conducted. The structure of the chapter follows six main components: (1) research design, (2) data collection procedures, (3) sampling strategy, (4) data analysis, (5) ethical considerations, and (6) methodological limitations.

3.1 Research Design

The study adopts a qualitative and exploratory research design, aiming to explore the perceived benefits and challenges associated with the implementation of AI in organizational contexts. This approach was chosen due to the complexity and contextual nature of AI adoption processes, and the need to obtain in-depth insights from professionals actively involved in this field. Semi-structured interviews were selected as the primary data collection method, allowing for both consistency across interviews and the flexibility to explore emerging topics.

According to (Magaldi et al., 2020), semi-structured interviews are suitable for exploratory research, tend to be based on a script or guide, and offer flexibility and adaptability while maintaining a focus on core themes. As (Langley et al., 2020) argue, this method also enables researchers to thoroughly analyze the study's subject while gathering data and in-depth information from interviewees.

3.2 Data Collection Process

A total of 20 semi-structured interviews were conducted between November 11th, 2024, and January 27th, 2025. Nineteen interviews were carried out via videoconference (Microsoft Teams), and one was conducted in person. Interview durations ranged from 20 to 71 minutes. Participants were contacted primarily through LinkedIn (Appendix A): 93 professionals were added as connections, 62 direct messages were sent, 5 declined the invitation, 5 initially responded but did not follow up, and 16 agreed to participate. The remaining 4 participants were approached through informal, personal channels.

The interview script (Appendix B) was designed based on the study's research objectives and consisted mainly of open-ended questions to elicit rich, unbiased responses. Interviews were conducted in Portuguese, recorded with participant consent, and later transcribed and translated into English for analysis.

3.3 Sampling Strategy

A purposive sampling approach was used to select participants whose professional roles involved artificial intelligence, data analytics, or related technological domains. The selection criteria included experience working directly with AI-related projects, and the public availability of professional information (e.g., on LinkedIn) to verify this experience. The sample was composed of professionals from diverse sectors, including technology, automotive, wine production, healthcare, insurance, and others to ensure a broad spectrum of perspectives.

Diversity was also considered in terms of hierarchical levels, including both operational and leadership roles. This heterogeneity aimed to enrich the analysis by reflecting various organizational experiences and viewpoints on AI implementation. A detailed description of the sample is provided in Table 1, and its composition by role is visualized in Figure 1.

#	Position	Role	Company affiliation in years	Industry experience in years
1	Data Engineer		3	4
2	Associate		3	3
3	Advisor		1	1
4	Analyst	Operational	1	1
5	ML Engineer		3	4
6	Consultant		1	1
7	Consultant		1	4
8	Chief Data Officer		2	12
9	Engineer Director		13	17
10	Innovation Specialist		6	7
11	Data Scientist		4	5
12	Senior Manager		12	12
13	Managing Director		18	29
14	ML Engineer, Founder	Leadership	1	4
15	Go-to-market leader		11	20
16	Head of Center		9	31
17	AI Product Owner		6	6
18	Head of Unified Communications		20	21
19	Dental Clinic Director, Founder		3	8
20	Technical specilist		6	8

Table 1 - Interview sample role description

As (Ma et al., 2021) note, individuals in higher organizational roles often possess strategic insight and deep knowledge of their institutions, offering valuable perspectives not only on operational aspects but also on broader institutional, financial, and policy-related dimensions.

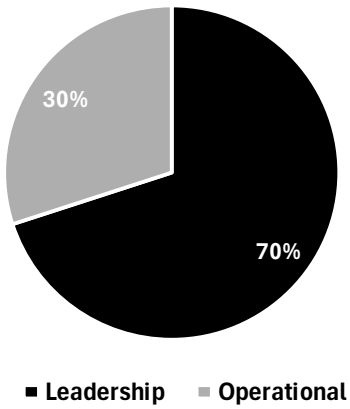

Figure 1 - Distribution between leadership and operational roles

3.4 Data Analysis

All interviews were transcribed manually and subsequently coded using NVivo 14. The analysis followed a thematic approach, using both deductive codes (informed by the literature review) and inductive codes (emerging from the interview data). Coding was reviewed twice to ensure consistency and alignment with the research objectives. Selected quotes were included in the results chapter to support key findings and enhance transparency in the interpretation of participant responses.

To ensure the reliability and validity of the analysis, several procedures were adopted. Transcriptions were reviewed in detail, coding was systematically applied and validated, and triangulation was used by comparing the insights of participants across different industries and organizational roles. This approach helped verify the consistency of emerging themes and reduced the risk of sector-specific or role-based bias, thus strengthening the credibility of the findings. These steps aimed to strengthen the credibility and trustworthiness of the findings.

3.5 Ethical Considerations

All participants received a brief description of the study's objectives, goals, and institutional affiliation (Appendix C). Informed consent was obtained from all interviewees before the interviews. They were informed about the voluntary nature of their participation, their right to withdraw at any moment, and the assurance of anonymity and confidentiality. No personally identifiable information is presented in this study, and ethical standards established by the hosting university for research involving human subjects were strictly followed.

3.6 Methodological Limitations

While the study employed rigorous methods, several limitations must be acknowledged. The sample size (n=20) may limit the generalizability of the results. Additionally, the reliance on LinkedIn for participant recruitment may introduce selection bias, favoring individuals with higher visibility or activity on professional networks. Another limitation stems from the language translation of the interviews, where subtle nuances in participant expression may have been lost. These constraints were taken into account in the interpretation of the findings.

Chapter 4
Results

This chapter presents the results derived from the interviews conducted with key participants.

The main objective was to create an appropriate environment for participants to share their views and thoughts and to understand the context behind some of their responses. Each section of this chapter details the findings related to the objectives of each question.

As depicted in the figure 3 below, most interviewees identified organizational factors as the predominant element influencing the implementation of AI, followed by social, technological, and financial factors, respectively.

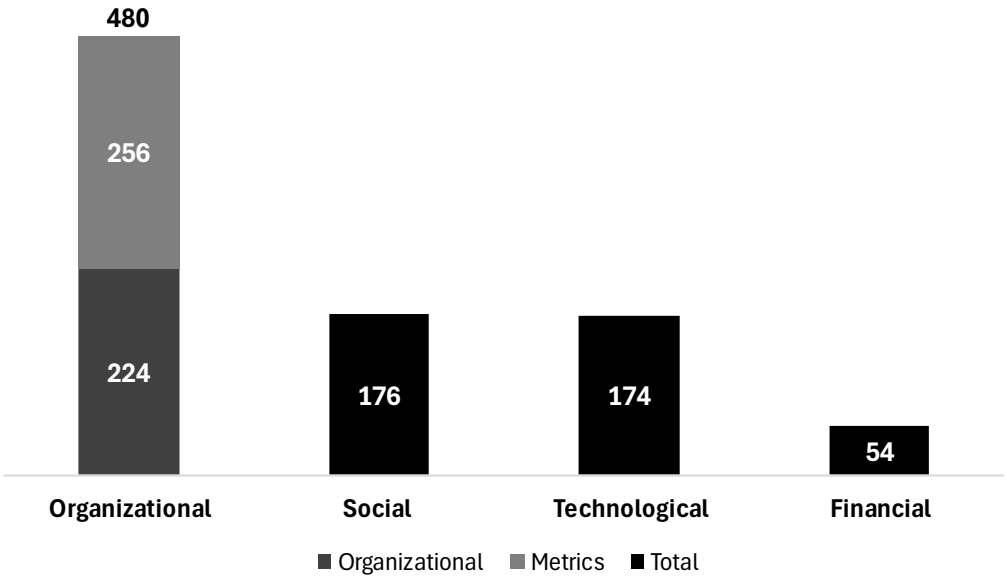

Figure 2 - Theme absolute frequency in interviews

4.1 Organizational Factors

Organizational themes emerged as the most prevalent in this study, encompassing a variety of subjects on how internal factors influence AI implementation.

4.1.1 Use of AI tools

One of the most discussed topics was the actual use of AI tools in the workplace. Among the tools mentioned, Microsoft Copilot was the most frequently used. It was primarily leveraged to enhance productivity and efficiency, especially in tasks such as summarizing documents and overcoming the so-called "white canvas syndrome." As participant L13 described, "PowerPoint presentations are a great example of this, because sometimes we spend hours formatting one (…). We provide the premises, the themes and subthemes, and based on that, the AI generates the presentation within the company's layout."

Another common use case was meeting summarization. Participant L15 highlighted how this functionality allowed latecomers to quickly get up to speed without disrupting the flow of discussion: "in under a minute, it gives me a summary of what has been discussed so far, saving me from asking repetitive questions like: *'Have you already talked about this?*' or *'Sorry, I'm not up to speed because I joined late*.' It instantly gives me a solid foundation to get up to speed and follow the meeting." He further added, "this kind of tool massively improves productivity and efficiency. On top of that, at the end of the meeting, Copilot generates a summary with the next steps, deadlines, and who's responsible for each task, which makes organization much easier."

4.1.2 Training, Literacy, and Change Management

Another central theme was the need for education and training to facilitate AI integration. Participants frequently compared the AI learning curve to the early days of personal computing. As participant L13 put it, “They must learn and recognize that the use of artificial intelligence today is as essential as learning to use Microsoft Office was some years ago.”

AI literacy was also framed as a foundational requirement for progress. As participant L2 noted, “If a person lacks literacy in this area, it also becomes a very significant barrier to projects.” In response, participant L15 described an approach to support adoption through peer advocacy: “what we do is to create 'champions' within each area — people who explore the technology first and then help other employees by showing them how it has been beneficial for them,” emphasizing a peer-to-peer learning dynamic and the importance of what he called a “positive contagion effect.”

Resistance to change was widely recognized as a challenge. Participant L16 captured this sentiment: “organizations and their processes are built by people, and people are harder to change than systems.” He continued, “It’s essential to ensure that they trust what we’re creating and feel comfortable letting go of processes they’ve been doing a certain way for ten years in order to adopt something new.” Participant L12 echoed this view, stating, “the implementation sometimes ceases to be so technical (…) we need to have the people innovating, relearning how they can interact with these technologies.”

4.1.3 Risk Aversion and Leadership Support

Risk aversion also emerged as a prominent barrier. Participant L2 explained, “if a company doesn’t have a culture of organizational entrepreneurship people tend to be very conservative (...)”, but clarified, “But it’s not really the people’s fault, people respond to incentives.” This highlights the role of organizational

systems and incentives in either promoting or hindering innovation. Participant O17 added that many CEOs hesitate to act first: “This looks really interesting, but let’s wait and see how it goes for others first,” illustrating how caution at the top can delay adoption.

By contrast, leadership support was consistently cited as an essential enabler. Participant L8 noted that it was “crucial to have top-down sponsorship,” emphasizing how strong executive backing eased the uncertainty surrounding the adoption of new technologies.

4.1.4 Implementation Strategies

Participants also discussed how AI should be introduced. Many agreed that waiting for perfect conditions is counterproductive. As participant L15 stated, “if we wait for the ideal scenario, where everything is perfectly organized, we end up missing out on the opportunities that already exist today.”

Proofs of concept were widely used to mitigate risk. Participant L12 explained, “a lot of enterprises start with a proof of concept and, once they realize it makes sense, they evolve towards a production-ready solution.” Participant L15 added that “the right strategy is to segment the projects and identify quick and effective opportunities,” suggesting that incremental implementation allows for better resource allocation and less disruption to existing workflows.

A distinction was made between public and private sector efforts. Participant O6 characterized the AI strategy in governmental organizations as “conservative” due to a “lack of organization and diligence when thinking about the future.” Participant L15 elaborated, “if a private company doesn’t innovate it might go out of business and disappear, whereas cabinet ministries will always exist,” highlighting the absence of competitive pressure in the public sector.

4.2 Social Factors

The social dimension of AI implementation encompasses how people perceive, accept, and adapt to new technologies in the workplace. It includes issues such as fears around job displacement, the need for continuous learning, shifts in hiring practices, and the broader cultural response to change. These factors are particularly relevant because they influence not only adoption at the individual level but also the collective success of organizational change initiatives.

Several interviewees emphasized that social acceptance and employee engagement are just as critical as technological readiness. While some ideas such as the need for training or managing resistance also appear in the organizational dimension, their recurrence in this section is intentional: they emerge here from a people-centered perspective, where the focus is on individual roles, workforce emotions, and societal implications.

4.2.1 Fear of Displacement and Workforce Restructuring

A major theme across the interviews was the concern about AI replacing human workers. This fear, while prevalent in public discourse, was not widely corroborated by participants. In fact, a majority reported no direct cases of layoffs resulting from AI adoption.

Participant O17 confirmed, "I'm not aware of any case where there was a reduction in the workforce directly linked to the implementation of AI." Similarly, participant L12 stated, "I haven't seen it directly affect anyone to the point where they stopped doing their job or were displaced because of AI." These statements help dispel the perception that AI implementation necessarily results in job losses.

Some interviewees described workforce expansion, rather than reduction. Participant L2 noted that "all the people involved in the development project

increased, from product owners to more technical roles like data engineers, data scientists, and machine learning engineers. This entire cluster of tech professionals grew." These comments reflect AI's potential to create new, high-value jobs, especially in technical fields.

However, other participants acknowledged that AI is likely to lead to job transformation over time. Participant L7 remarked, "we never had any cases of layoffs due to automation. People were always reassigned to other roles, often to less repetitive and more strategic tasks." Similarly, participant O6 stressed that displacement is not immediate: "a machine learning model doesn't suddenly get implemented (…) and people are let go. That's not something we're seeing."

The overall picture is one of restructuring rather than replacement. AI is prompting shifts in roles and responsibilities, but not necessarily eliminating positions, at least not in the short term.

4.2.2 Reallocation and the Rise of More Strategic Roles

Participants highlighted that, in many cases, AI relieved employees of low-value, repetitive tasks. In these situations, staff were reallocated to more strategic or meaningful functions.

Participant L15, who worked with a government department responsible for reimbursing healthcare costs, emphasized the benefits of reallocation: "tasks that are so repetitive and routine that it's hardly prestigious to have a human assigned to them" were reassigned, allowing employees to focus on more impactful work.

Participant L13 shared a related story about a translator in his company: "She's already realized this and is currently reinventing herself and repositioning to find a new role within the company." The theme AI as a catalyst for professional reinvention was repeated by several others. According to L15, "people are freed up to take on other tasks within the company. They end up realizing that AI can

help them reinvent themselves within their roles. And I don't see people getting frustrated, on the contrary, it's increasingly becoming common sense."

Taken together, these accounts suggest that AI can be a tool for empowerment, enabling employees to move toward more fulfilling and strategic roles when supported by the right organizational conditions.

4.2.3 Changing Hiring Practices

Although layoffs were rare, some participants pointed to reduced hiring needs as a likely long-term consequence of AI adoption.

Participant L4 noted that "what's more likely is that companies reduce new hiring. (…) Now, with AI, companies can scale without proportionally increasing the number of employees." While this is not yet a widespread trend, it suggests that AI could lead to gradual changes in organizational growth models, particularly in operational and administrative areas.

This shift reinforces the need for companies to plan ahead, not only for internal workforce reallocation, but also for changes in talent acquisition and workforce planning.

4.2.4 Upskilling and the Role of Education

The need for continuous learning and skill development was a consistent message across the interviews. Participants emphasized that, in the face of evolving technologies, upskilling is not optional but essential.

Participant L16 explained that within his organization, "there's also a constant focus on upskilling and qualifying people." He and others underlined that training initiatives must be proactive, not reactive, especially as the pace of AI development accelerates.

Participant L15 offered a memorable quote that captured this idea: "It's not AI that will take people's jobs, it's someone who knows how to leverage AI that will

replace someone who doesn't." He compared the situation to earlier resistance to computers, where those unwilling to adapt eventually fell behind.

The role of academic institutions was also raised. Participant L16 stressed the need for a systemic approach: "we need to think about the reskilling of workers and the role of universities in that process." Participant L20 reinforced this, stating that adapting to technological change "doesn't depend solely on companies, but society as a whole needs to prepare for these changes."

These insights suggest that AI-readiness is a shared responsibility, requiring cooperation between companies, employees, and educational institutions.

4.2.5 Rethinking the Social Contract

While job loss due to AI was not commonly reported among participants, concerns about the evolving nature of work were widespread. The findings point toward a broader restructuring of job roles, expectations, and skills rather than mass layoffs.

Interviewees consistently portrayed AI as an opportunity for employees to elevate their roles, provided they have access to training, support, and forward-looking leadership. Hiring practices may evolve, and pressure on education systems to prepare future workers is expected to increase.

In short, the social dimension of AI adoption is less about replacement and more about reinvention. When combined with the right cultural and institutional support, AI has the potential to enhance, not diminish, human work.

4.3 Managing Expectations Around AI

A recurring theme in the interviews was the gap between what users expect AI tools to do and what those tools can actually deliver. This "expectation gap" can undermine adoption, lead to user frustration, or even cause premature abandonment of the technology. This section explores the main sources of these

misaligned expectations, how organizations are managing them, and the role of technical transparency in building trust.

4.3.1 Unrealistic Expectations and Initial Disappointment

Many participants described how overhyped expectations, often shaped by media narratives or early contact with powerful tools like ChatGPT, led to disillusionment once AI was deployed in real work environments.

Interviewee L10 reflected on this dynamic: "This is going to be super easy to work with, we'll just type in any prompt, and it'll do everything by itself — But quickly ran into some challenges, because it wasn't delivering exactly what it had promised." Her experience illustrates how early enthusiasm can turn into frustration if organizational onboarding does not calibrate expectations.

Participant L18, who works with AI-based customer service tools, confirmed this trend: "one of the biggest challenges right now" is managing expectations because users compare internal tools with public-facing models like ChatGPT, which often seem more capable and refined.

These cases suggest that expectation management is not just a communication issue — it is critical to user adoption and trust.

4.3.2 The Role of Media and Public Perception

Some participants connected this issue to how AI is portrayed in the media and popular discourse. Participant L4 noted that "there's a gap between what people think is possible and what actually is. And that goes both ways, sometimes they overestimate, sometimes they underestimate."

He gave a practical example of media distortion: "people might read something on the news like 'AI can detect cancer before it happens.' But they don't know that that outcome often occurs under very specific and non-generalizable conditions." Participant L5, who works in the same field, reported

facing similar struggles in educating clients about what AI systems can realistically achieve.

These observations point to a broader challenge: public narratives about AI often set unrealistic benchmarks, especially in commercial or corporate contexts where use cases are more constrained.

4.3.3 Technical Transparency and User Trust

Several participants stressed the importance of transparency as a tool for managing expectations and building trust. Participant L11 emphasized that "showing the actual data the model used to generate a given result, providing references, or even including charts that explain what happened, gives users more confidence, because they can consult and validate the information if they want to."

This insight highlights a practical path forward: building interfaces and workflows that expose the logic behind AI decisions in ways users can understand. Transparency transforms the tool from a mysterious "black box" into a more predictable system.

Interviewee L12 added that this trust-building process can be staged: "having an initial high level of human supervision" helps in the early stages of adoption, and "may decrease as trust in the technology grows."

These perspectives reinforce the idea that adoption is a process of gradual confidence-building, not a one-time rollout.

4.3.4 Expectation Management as a Strategic Capability

The interviews reveal that unrealistic expectations, often shaped by media hype or initial interactions with public models, can hinder AI adoption. When tools underdeliver compared to what users imagined, trust erodes quickly.

To address this, organizations must treat expectation management as a continuous process. Transparency about how AI works, combined with early-stage supervision and clear communication, helps build user confidence and supports long-term adoption.

4.4 Technological Factors

Technological readiness is widely acknowledged in both literature and practice as a foundational requirement for AI implementation. In this study, technological challenges emerged as the second most frequently mentioned barrier, just behind organizational factors. Participants frequently pointed to the quality of data infrastructure, system integration, and regulatory compliance as critical success factors, or points of failure, in AI initiatives.

4.4.1 Data Infrastructure and System Maturity

Nearly two-thirds of participants mentioned data quality and infrastructure as a central concern. Participant L13 stressed that for AI to succeed, companies must "make the right decisions," including ensuring "a good data infrastructure, real-time data collection, and organizing data correctly."

Interviewee O17 emphasized, "The way a company's data is organized is fundamental. If the data isn't reliable, coherently structured, and stored within an organized and secure architecture, building AI models becomes difficult. As the saying goes, *garbage in, garbage out*."

Several participants described encountering fragmented systems, outdated data pipelines, or siloed platforms, which hindered the development of scalable AI solutions. Participant O9 reported that "the main obstacle to large-scale AI adoption is that there is no infrastructure to support it, the databases are very outdated, poorly connected, and it is not possible to have a unified view of each customer's information."

These testimonies align with the view that AI cannot simply be "plugged into" an existing system, it depends on a clean, unified, and accessible infrastructure. The lack of such a foundation often leads to stalled or failed initiatives.

Figure 4 illustrates the requirements needed to reach AI capabilities represented by the top of the pyramid

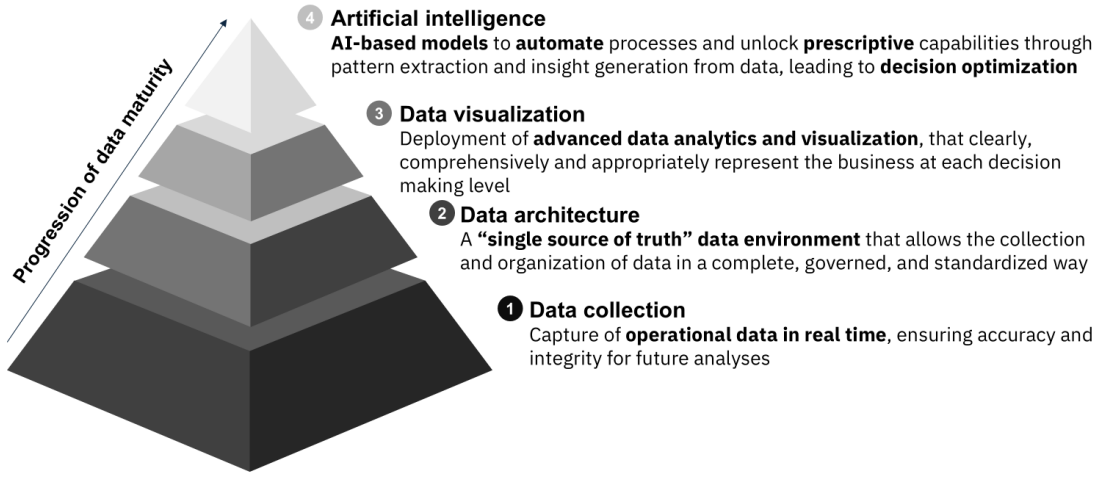

Figure 3 - AI required data infrastructure illustrated as a pyramid

4.4.2 System Fragmentation: Real-World Examples

To help illustrate what a lack of structure means in practice, some participants provided concrete examples. Participant L16 described a multinational insurance company where "data from the branch in Angola is structured one way… the data from the branch in Portugal is organized in a completely different manner." These inconsistencies, combined with incompatible software suites, made it nearly impossible to deploy a model across regions.

In another case, participant O6 reported that an entire government agency's operational data was stored in a single Excel file, often populated manually or left incomplete. These examples show how poor foundational systems, not a lack of AI itself, are the real bottlenecks.

4.4.3 Data Visibility and C-Level Awareness

Several participants emphasized that executives often underestimate the state of their organization's data. As participant O17 noted, "companies often have no idea how disorganized their data really is," unless data management is explicitly prioritized at the leadership level.

Participant L5 explained that if a company's infrastructure is not sufficiently mature, his team will not proceed with the AI implementation. "We've had to decline projects because the data quality just didn't meet the basic requirements," he said. This reflects a growing trend of data maturity becoming a go/no-go criterion in AI project selection.

4.4.4 Regulatory Constraints and Privacy by Design

Data protection and regulatory compliance were also frequently cited as major constraints, especially in sectors like public administration and healthcare. Participant L15 stated, "sectors like public administration, regulatory bodies such as the Bank of Portugal, and areas related to defense are much more sensitive when it comes to adopting AI."

A common barrier is uncertainty about what regulations allow, even when clear rules already exist. This lack of clarity can delay adoption or lead to over-cautious risk aversion.

Participants L12 and L8 stressed the importance of the AI Act, which "defines what can and cannot be done in certain contexts when using artificial intelligence," and having rigorous processes for assessing AI-related risks in line with European regulations.

These interviews suggest that regulatory literacy is as important as technical literacy when deploying AI in sensitive domains.

4.4.5 Privacy Risks

Concerns over privacy were nearly universal, though participants diverged in their responses. Participant O17 warned that "unless there are specific security safeguards in place, [data] can be used to train the model," when input into public systems like ChatGPT. He explained this as one of the key reasons why "many companies choose to develop an internal GPT model," allowing them to protect proprietary information while leveraging their own internal knowledge base.

Participant L18 raised the issue of "black box commercial models" used in business services, such as virtual assistants and chatbots. For companies that serve other companies, using external tools creates compliance risks that are harder to mitigate. As he put it, "we have to ensure that no sensitive user information is being fed to external models."

These concerns led many participants to adopt a "privacy by design" approach, favoring internal development, limited integrations, or controlled access environments to ensure GDPR compliance.

4.4.6 Infrastructure First, Innovation Second

Across all interviews, a consistent message emerged: AI depends on infrastructure. Participants repeatedly emphasized that without robust, well-structured, and accessible data systems, even the most advanced AI tools are ineffective.

Moreover, technology challenges are not just technical, they are strategic. Leadership awareness, regulatory knowledge, and privacy safeguards are all part of the equation. Organizations that overlook these foundational requirements risk not only failure but also reputational and compliance setbacks.

In short, AI adoption begins with data maturity. Without it, innovation cannot scale.

4.5 Financial Factors

Although financial limitations are often cited as key obstacles to technological innovation, this study found that cost alone is rarely the decisive factor in the success or failure of AI initiatives. Instead, participants emphasized the importance of demonstrating value, managing long-term return on investment (ROI), and tailoring solutions to fit available resources.

While financial concerns were mentioned less frequently than organizational or technological factors, they remain an important consideration, especially for smaller companies and cost-sensitive sectors.

4.5.1 Cost as a Barrier, But Not the Main One

Only a few interviewees described cost as the primary obstacle to implementation. Participant L4 argued that "cost is not always the main barrier," stressing instead the importance of proving the value generated by the technology.

Participant O1 reported that in large corporations, budgets were generally sufficient to absorb AI-related costs. However, this was not the norm for most organizations, particularly SMEs, which often need to manage limited budgets carefully.

These examples show that for larger organizations, budget availability may not be the limiting factor. However, in other cases, particularly in small and medium-sized enterprises (SMEs), financial capacity remains a legitimate concern.

4.5.2 Cost Management Through Phased Implementation

While the strategic value of proofs of concept (PoCs) was previously highlighted as a way to reduce organizational resistance and facilitate gradual adoption (Section 4.1.4), several participants also emphasized their role in

managing financial exposure. By testing AI solutions on a smaller scale, organizations can assess feasibility and value without committing significant upfront investment.

Participant L12 explained, "a lot of enterprises start with a proof of concept and, once they realize it makes sense, they evolve towards a production-ready solution." Similarly, L15 noted the importance of identifying "quick and effective opportunities," which could deliver early results and build a stronger case for additional funding.

This approach allows companies, especially those with constrained budgets, to reduce the financial risks associated with innovation. PoCs act as cost-control mechanisms, providing real-world validation that can justify future investment or signal the need to pivot early.

4.5.3 Developer vs. End-User Perspectives

The interviews highlighted a fundamental distinction between organizations that develop AI models and those that use AI products and services. The financial challenges differ between these two groups.

Participant L18, who works at a company that develops AI tools, noted that "creating large-scale AI models is only available for a couple of huge companies with higher capex spending." His organization decided to stop building its own models and instead integrate existing ones: "We sell that as a service, reducing entry costs, allowing companies to access the technology at a reduced price."

Participant L16 described a similar trade-off in the context of customer service: "AI doesn't sleep or eat, neither does it need continuous education." However, he acknowledged that running large commercial models for every client interaction "could be more expensive than paying operators' salaries." To balance this, his team invested time in testing different business cases and their economic viability, and created a blend of hybrid models, combining larger

models such as OpenAI's and other smaller internal models, tailored to specific needs.

These perspectives illustrate how flexibility in AI architecture, combining internal, external, and open-source models, can reduce total cost of ownership and improve affordability.

From the end-user perspective, licensing costs were a frequent concern. Participants L13, O14, and L10 mentioned these costs as a limiting factor in broad deployment.

Participant L10 explained that "the price of licenses led to creating a test group to assess the tool's utility before committing to buying more licenses for the whole company." This cautious approach illustrates how organizations balance access with financial prudence.

In sectors like healthcare, cost barriers were even more pronounced. Participant L19, a medical professional, stated that while AI is not new in her field, "the cost of certain software is still prohibitive to many clinics."

These cases show that while licensing costs may not prevent initial experimentation, they often limit scalability and accessibility, especially in public or resource-constrained environments.

4.5.4 Infrastructure Investment

Several participants emphasized the high infrastructure costs associated with AI, including computing power, cloud services, and GPUs. Participant L15 noted that despite increased competition and efficiency, "the infrastructure required to run these models still implies massive investments."

This reinforces the idea that hardware and back-end capacity can be just as limiting as software licenses, especially for organizations looking to move from PoCs to full-scale deployment.

4.5.5 Value Over Volume

Overall, participants portrayed financial constraints not as insurmountable barriers, but as conditions that require smart design choices. Proofs of concept, hybrid models, service-based offerings, and licensing pilots were all used to reduce or manage costs while demonstrating value.

The most consistent message was this: cost is only a barrier when value is unclear. Organizations that focus on business impact, ROI, and strategic alignment are more likely to justify AI investment, even with limited budgets.

4.6 Measuring AI's Impact

Assessing the impact of AI is a critical, yet underdeveloped area across most organizations. While participants acknowledged clear productivity and efficiency gains, many also admitted that formal measurement frameworks are still lacking. This section explores the current methods used to evaluate AI initiatives, both quantitatively and qualitatively, and highlights the limitations and emerging efforts to improve impact assessment.

4.6.1 Informal and Qualitative Assessments

A majority of participants stated that AI's impact was primarily assessed through informal feedback. This is especially common in early-stage implementations or when tools are used at the individual or team level.

Multiple participants shared the same issue as participant L10, who noted, "we have yet to have concrete data allowing us to objectively measure benefits achieved from the implementation of AI." Still, she emphasized the usefulness of informal feedback, explaining that employees often share comments like, "I have used this prompt with this tool, and it did a wonderful job summarizing a meeting" or "I can now write emails much faster."

Such feedback offers insights into user satisfaction and perceived productivity gains, but lacks the rigor required to make broader strategic decisions.

4.6.2 Quantitative Metrics

Despite the limitations above, several organizations have begun to apply quantitative methods, particularly in use cases with clear before-and-after comparisons.

Participant L16 described how AI was used to automate accident report processing at an insurance company: "clients [now] receive accident report responses in minutes instead of days," which translated into measurable gains in customer satisfaction and likely improvements in Net Promoter Score (NPS).

Participant L18 noted that their chatbot now handles "more than 40 percent of customer interactions automatically," reducing both response time and labor costs. Likewise, L15 reported that AI helped reduce effort in routine tasks by "80 percent," and that "50 percent of tickets [were] being addressed autonomously" at a government agency.

Participant L13 shared a financial outcome: by implementing a price optimization model in a single department, the company saved "more than €1.2 million," calculated based on labor cost savings. He also mentioned another project in which user experience metrics were collected to assess how clients perceived AI-generated interactions: "more than 80 percent of clients who spoke with the machine believed they were talking with a human."

These examples demonstrate that when the right data exists, AI impact can be measured in terms of time, money, and quality of service. However, this was more common in operational contexts with structured workflows.

4.6.3 Scientific Models and Long-Term Evaluation

A small number of participants reported efforts to build more formalized and scientific approaches to impact measurement. Participant L16 mentioned that his company was collaborating with a university on a PhD project focused on developing "a scientific model to measure AI's impact."

This initiative reflects a growing recognition that standardized, academic frameworks are needed to properly assess how AI affects performance, strategy, and even organizational culture over time.

Participant L11, for example, shared how his team tracked AI training quality using accuracy metrics: comparing how often the algorithm provided the right answer versus how often it failed, and how badly, giving insights on the model's precision level until it reached the desired level. Meanwhile, participant O17 described a method of tracking user productivity through "mouse cursor movement monitoring" to quantify time savings in a task-by-task analysis.

These examples illustrate that while advanced measurement approaches are emerging, they remain the exception rather than the rule.

4.6.4 Measuring What Matters, But Inconsistently

The evidence suggests that while many organizations recognize the value of measuring AI's impact, few have adopted standardized or structured methods to do so. Informal feedback remains the dominant evaluation method, particularly for early-stage or knowledge-worker applications.

However, in more technical and repetitive contexts, such as customer service, pricing, or document processing, organizations are increasingly using quantitative metrics to track efficiency, cost reduction, and user satisfaction.

Emerging academic collaborations and experimental methods show promise for long-term evaluation frameworks, but for now, impact measurement remains inconsistent and fragmented across the corporate landscape.

4.7 Synthesis Table

To conclude this chapter, the table below synthesizes the main insights collected from the interviews across the four dimensions explored: organizational, social, technological, and financial. Each theme is presented with a summary of the most common perspectives and corresponding observations. This synthesis serves both as a recap of the results and a foundation for the discussion that follows in Chapter 5.

Dimension	Theme	Summary of Key Findings
Organizational	Use of tools	AI tools (e.g., Copilot) are widely used for productivity, summarization, and content generation
	Training and literacy	Lack of AI literacy is a critical barrier; peer-driven initiatives like "champions" are effective
	Resistance and risk aversion	Resistance to change is common; risk-averse cultures and lack of incentives slow adoption
	Leadership and implementation	Leadership support is essential; PoCs are used to build internal trust and reduce disruption
Social	Job displacement and reallocation	No major layoffs observed; AI is prompting role evolution and reassignment to higher-value tasks
	Hiring and workforce planning	AI may reduce future hiring needs; organizations are scaling without proportionally increasing headcount
	Upskilling and education	Upskilling is necessary; participants call for stronger involvement from universities and society
Technological	Data infrastructure and maturity	Data fragmentation and poor infrastructure are key barriers; clean, integrated systems are required
	Visibility and executive awareness	Executives often underestimate data quality issues; C-level engagement is essential
	Regulation and privacy	Compliance with GDPR and the AI Act is vital; internal models are preferred for sensitive data
Financial	Cost barriers and priorities	Cost alone is rarely the main barrier; value justification is more important than price
	Implementation strategies	PoCs and phased rollouts help reduce risk and manage limited budgets effectively
	Licensing and infrastructure	Licensing costs limit scale; infrastructure costs (e.g., GPUs, servers) are significant
Cross-Cutting	Impact measurement	Most rely on informal feedback; only a few use structured KPIs or collaborate with academia

Table 2 - Synthesis of interview findings by dimension

The findings presented throughout this chapter highlight that while AI is being adopted across a range of industries, its successful implementation depends on the interplay of cultural readiness, technical maturity, financial planning, and human engagement. These factors do not operate in isolation, many are interdependent and must be addressed in a coordinated way.

The next chapter will interpret these findings in light of the existing literature, discussing where the results confirm, challenge, or expand on current academic understanding.

Chapter 5
Discussion

This chapter critically interprets the empirical findings outlined in Chapter 4 in light of the literature review (Chapter 2), highlighting convergences, contradictions, and new insights. It moves beyond confirmation of known dynamics, drawing attention to emerging themes and practical implications for AI adoption across organizations.

5.1 Organizational Dynamics

Organizational factors emerged as the most influential elements in AI implementation, aligning closely with existing research (Kaggwa et al., 2024; Merhi et al., 2024). However, this study nuances that understanding by revealing how leadership support must be accompanied by structured strategies, such as the designation of internal AI "champions" to catalyze peer learning and cultural transformation.

Contrary to some traditional views that resistance stems solely from fear of replacement, this research finds that resistance is often structural, arising from risk-averse cultures and legacy incentive systems. Although the literature discusses "organizational inertia," this study highlights a more subtle mechanism: employees often recognize the value of AI but lack incentives or confidence to act without top-down sponsorship. In this sense, leadership does not merely guide change but must proactively de-risk innovation for middle layers of the organization.

Interestingly, the contrast between private and public sectors revealed in interviews also adds a novel dimension. While previous literature has acknowledged bureaucratic constraints, this study deepens that observation by

linking it to the absence of competition and urgency in the public sector, reinforcing the notion that market pressure acts as an informal accelerant for innovation.

5.2 Social Expectations and Workforce Transformation

While prior literature has largely focused on workforce displacement as a risk, this study finds little empirical support for that concern, at least in the short term.

Participants consistently reported job transformation and reallocation, not elimination, a finding that supports emerging evidence from real-world contexts (World Economic Forum, 2025).

Where this study contributes uniquely is in framing AI not just as a tool for automation, but as a catalyst for professional reinvention. The concept of "positive contagion" where early adopters influence their peers, emerged as a grassroots mechanism for change that is underexplored in academic research.

Participants revealed that inflated perceptions of AI capabilities, fueled by media narratives and public-facing tools, often led to frustration and disengagement when enterprise solutions fell short. Unlike technical constraints, these emotional and cognitive mismatches have received limited attention in the literature. This study suggests that managing expectations should be treated as a core competency in digital transformation initiatives.

5.3 Technological Readiness, Data Maturity, and Privacy

Technological barriers were extensively documented in previous studies (Mikalef et al., 2019), particularly concerning data quality and infrastructure. This study confirms those concerns but extends them with practical illustrations, from Excel-based databases to cross-national data fragmentation, that vividly expose the operational realities behind abstract concepts.

More importantly, this study introduces the notion that technological readiness is inseparable from organizational awareness. Several participants noted that C-level leaders often underestimate the poor state of their data ecosystems. Thus, technological barriers are not merely technical, they are managerial. This finding bridges the technical-organizational divide and calls for greater C-level literacy in data architecture.

In terms of privacy and compliance, the study confirms known risks but also signals a trend toward internal AI development as a strategy for risk mitigation, particularly by larger firms. This points to an emerging bifurcation in AI strategy: large firms build private models to ensure control, while smaller firms must navigate trade-offs between accessibility and data exposure.

5.4 Financial Considerations: Cost, Value, and Strategic Framing

While AI implementation does require significant financial investment, participant feedback suggests that cost, by itself, is not an absolute barrier. Instead, the findings suggest that cost concerns become surmountable when AI initiatives are framed in terms of strategic value. This aligns with literature that frames AI investment as long-term and strategic (Kamoonpuri & Sengar, 2023).

Where this study innovates is in documenting hybrid financial strategies, such as combining proprietary and third-party models, to reduce cost without compromising performance. The distinction between AI developers and AI users was also noted, with each group facing different cost structures and risk exposures.

Ultimately, this research reinforces that the question is not whether AI is affordable, but whether it delivers visible value. In this sense, proofs of concept (PoCs) serve not just as technical tests but as business cases, validating both cost and organizational alignment.

5.5 Measuring AI Impact: Current Practices and Future Directions

A final area of contribution lies in how AI impact is assessed. While traditional studies emphasize quantitative metrics (Ransbotham et al., 2017), this study reveals that most organizations still rely on informal feedback and anecdotal evidence. Despite this, several participants are experimenting with structured evaluation models, such as user productivity analytics, cost savings calculations, and academic collaborations to create formal metrics.

This suggests that impact measurement is an evolving field in its own right. The study argues that organizations must move beyond "ROI logic" alone and adopt multidimensional frameworks that account for learning, trust-building, and strategic alignment.

Chapter 6
Conclusion

In this chapter, the main aim is to summarize the findings provided by the results described above.

This study sets out to investigate the main drivers, benefits, barriers, and challenges associated with the implementation of Artificial Intelligence in organizations, across organizational, social, technological, and financial dimensions. By combining an extensive literature review with insights from 20 semi-structured interviews with industry professionals, the research provides a comprehensive and nuanced understanding of the current state of AI adoption.

6.1 Key Findings

The findings of this study are best understood in direct response to the two central research questions.

Regarding Research Question 1: "What are the main drivers and benefits that encourage organizations to implement AI across organizational, social, technological, and financial dimensions?" The study shows that leadership commitment, cultural adaptability, and investment in workforce reskilling emerged as crucial enablers. In the social domain, peer influence and expectation management proved vital, with AI often acting as a catalyst for role reinvention rather than job loss. Technological drivers included the presence of robust, integrated data infrastructure and organizational readiness to comply with evolving regulatory frameworks. Financially, organizations that viewed AI as a strategic, long-term investment and deployed cost-mitigation strategies, such as small-scale pilots and hybrid model architectures, were better positioned to capture value.

As for Research Question 2: "What are the primary barriers and challenges that hinder the implementation of AI in organizations across the same dimensions?" The study uncovered persistent organizational challenges such as resistance to change, lack of appropriate incentives, and the absence of clear internal alignment. Socially, unrealistic expectations and insufficient AI literacy were common hurdles. On the technological front, fragmented data systems, low executive awareness of infrastructure weaknesses, and privacy concerns constrained progress. Financially, limited access to resources, especially for smaller firms, combined with the difficulty of demonstrating short-term ROI, continued to restrict broader adoption.

6.2 Contributions to Practice and Research

This study contributes to the growing body of knowledge on AI adoption by mapping real-world drivers and barriers, offering grounded insights that confirm, challenge, and expand current theories. It highlights the practical role of expectation management and peer influence, adds clarity to how data readiness is often misunderstood, and illustrates the increasing reliance on hybrid AI models. For practitioners, the findings offer clear evidence that successful AI implementation depends not only on technological readiness but also on cultural transformation, leadership engagement, and careful management of financial and human resources. Moreover, the study underscores the importance of addressing the human dimension of technological change, emphasizing that AI's success is closely tied to employee engagement, training, and expectation management. These insights help bridge the gap between academic theory and practical application in the evolving landscape of AI adoption.

6.3 Limitations and Future Research

This study offers relevant insights into the adoption of AI in organizations; however, some limitations should be acknowledged. Although the sample included participants from Switzerland and France, most interviewees were concentrated in a single region, which limits the broader geographic generalization of the findings. Expanding the sample to cover a wider range of cultural and regulatory contexts would enhance the external validity of future studies.

Another limitation stems from the evolving nature of AI technologies and the relatively recent stage of many implementation projects observed. As a result, some long-term impacts and organizational transformations could not yet be fully assessed.

Future research could address these limitations by conducting longitudinal studies to capture the evolution of AI adoption over time. Comparative analyses across sectors, regions, and types of organizations would also provide richer insights. Additionally, the development of standardized methods to measure AI's organizational impact remains an important area for further investigation.

6.4 Final Reflection

Artificial Intelligence holds transformative potential, but its successful implementation depends on more than just technology. It requires cultural readiness, strategic vision, human adaptability, and organizational trust. By recognizing and aligning these dimensions, organizations can turn AI from a complex challenge into a competitive advantage. In an era defined by accelerating digital disruption, those who navigate AI with purpose and integrity will not only adapt but lead the next generation of organizational innovation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of my written thesis, *Challenges to the Implementation of AI in Organizations: An Empirical Analysis of Implementation Drivers and Challenges*, ChatGPT was used for the following tasks: translation and text revision, with the prompts used listed at the end of the document in the Prompts List section. After using these tools, 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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Prompts List

1. "I'm writing a master's thesis, rewrite this sentence in English in a clean and organized way. Use an academic tone."
2. "Translate this sentence to English."
3. "Give me multiple synonyms for this word."
4. "Give me a list of words to connect the different paragraphs to maintain a cohesive storyline."

Appendices

Appendix A – Interview Invitation

Good afternoon [Name of the person],

My name is Vasco, and I am a Master's student in Management at Católica Porto Business School. I am currently working on a thesis about the impact of artificial intelligence on business operations and strategy. I would like to hear your insights and experiences regarding the challenges and opportunities your organization has encountered when implementing this technology.

Would you be available for a short interview at a time that is most convenient for you?

I believe your experience could provide valuable input for my research. Thank you in advance for your consideration. I remain at your disposal to clarify any questions and to arrange the interview according to your availability.

Many thanks,

Vasco Silva

Appendix B – Interview Script

Questions
1. Background and Role of AI in the Organization
1.1. Can you briefly describe your role and how it involves AI?
1.2. How would you describe the role AI currently plays in your company/industry?
2. Challenges in AI Implementation
2.1. What are the biggest challenges in implementing AI in your organization?
2.1.1. Which dimensions are these challenges most related to? (e.g.: organizational, social, technological, financial, other)
2.2. Have you encountered any resistance to AI adoption in your company?
2.2.1. What are the main sources of resistance?
2.3. Does AI implementation depend on collaborations or partnerships? If so, which ones, and how do they affect the process?
2.4. How does your organization manage data for AI systems?
2.4.1. Do you face challenges related to data availability, quality, or privacy?
3. Benefits and Value of AI
3.1.What are the most significant improvements you have observed due to AI implementation? Can you provide a concrete example where AI has generated a specific benefit for your organization?
3.1.1. Has AI improved operational efficiency? How?
3.2. In which business areas has AI implementation delivered the highest return on investment (ROI)?
3.2.1. Is it possible to quantify these gains? What metrics or indicators do you use to measure AI's impact and success in your organization?
3.3. How has AI impacted employees in your organization?
3.3.1. Has it led to job displacement, reskilling, or the creation of new roles?
4. Future Trends and Strategic Impact of AI
4.1. Looking ahead, how do you see AI evolving in your sector over the next 5 to 10 years?
4.2. What emerging AI technologies or trends do you think will have the greatest impact on your sector?
4.3. In your opinion, what will be the biggest challenge for organizations as they scale AI solutions in the future?
5. Closing
5.1. Is there anything else you would like to add about AI's impact on your organization?

Table 3 - Interview questions guideline

Appendix C – Information for Participants

Information for participants

The objective of this interview, conducted as part of a Master's thesis in Management at Católica Porto Business School, is to engage with professionals experienced in the field of artificial intelligence, particularly those responsible for the implementation and use of these technologies in their companies, in order to understand their views on the drivers and challenges associated with AI adoption.

Confidentiality:

The Master's Thesis will be public. However, to ensure that neither the participant nor their employer is negatively affected by anything that may be said, all information and quotes from the interview will be anonymized to protect the identity of the participant and any individuals and/or companies mentioned.

Topics on AI implementation:

Some of the topics that may be discussed include:

- Your background and role within the organization in relation to the use of AI-related technologies.
- Your perception of the challenges associated with the use and implementation of artificial intelligence.
- Your perception of the gains and benefits associated with the use and implementation of artificial intelligence.
- Your opinion on the future of this technology.

Participation in the interview:

Participation in this study is entirely voluntary. You have the right to refuse to participate and the right to decline to answer any question.

Potential risks and strategy to minimize them:

There is a risk that I might misquote or misinterpret your statements. To prevent this, upon request I will share the interview transcript with you so you can review and correct it, if necessary, should you wish to do so.

By participating in the interview:

You will be contributing to research that aims to improve understanding of the factors influencing the adoption (or lack thereof) of this technology in companies. Your participation will be part of a Master's thesis and will contribute to the overall understanding of issues related to artificial intelligence adoption, helping to bridge the gap between academia and the corporate world.

Thesis Author,

Vasco Silva