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Implementing Artificial Intelligence systems in Supply Chain Management - AI design principles framework application

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Abstract

The growing adoption of artificial intelligence (AI) in supply chain management has emphasized the need for structured frameworks to effectively support AI project implementation. While the literature highlights significant potential benefits, many AI initiatives fail due to organizational and managerial challenges rather than technological limitations. In this context, this thesis aims to empirically validate and, where necessary, refine a theoretical framework designed to guide the implementation of AI projects in supply chain environments.

The framework analysed is derived from the study *"What could go wrong? Unlocking AI Potential in Supply Chain Management: Design Principles and Best Practices"* and is based on Critical Success Factors (CSFs) identified in the literature and organized into principles and conceptual pillars. To assess its robustness and applicability, a qualitative research approach was adopted, based on seven case studies collected through semi-structured interviews with professionals directly involved in AI projects across the supply chain.

The empirical analysis followed a two-step approach, combining within-case and cross-case analyses to identify recurring patterns and divergences. The results show strong empirical alignment with the framework, confirming the relevance of several principles as key enablers of AI project success. Principles that were inconsistently applied were often associated with inefficiencies or implementation challenges, further supporting the framework's validity.

In addition, two main deviations from the original framework emerged. First, the "Explainable and Transparent AI" pillar was not significantly adopted in the analysed cases, leading to its reinterpretation as a facilitating rather than enabling element. Second, the findings suggest revising the project timeline by positioning the creation of interdisciplinary teams prior to the resource assessment phase.

Overall, this thesis provides an empirically grounded contribution to the understanding of AI implementation in supply chain management, offering both a refinement of existing theoretical frameworks and concrete practical insights. From an academic perspective, the study strengthens the connection between theory and empirical evidence, contributing to the ongoing debate on critical success factors for AI projects. From a managerial standpoint, the findings provide actionable guidance for practitioners, supporting managers and decision-makers in structuring, managing, and successfully implementing AI initiatives within complex supply chain contexts.

Key-words: *Artificial Intelligence ; Supply chain ; Framework ; Critical success factor; Design principles; Industry 4.0*

Abstract in Italiano

La crescente adozione dell'intelligenza artificiale (AI) nella gestione della supply chain ha evidenziato la necessità di framework strutturati in grado di supportare efficacemente l'implementazione dei progetti di AI. Sebbene la letteratura metta in luce i potenziali benefici significativi di tali tecnologie, molte iniziative di AI falliscono a causa di criticità di natura organizzativa e manageriale piuttosto che per limiti tecnologici. In questo contesto, la presente tesi si pone l'obiettivo di validare empiricamente e, ove necessario, affinare un framework teorico progettato per guidare l'implementazione di progetti di intelligenza artificiale in ambito supply chain.

Il framework analizzato deriva dallo studio *"What could go wrong? Unlocking AI Potential in Supply Chain Management: Design Principles and Best Practices"* ed è basato sui Critical Success Factors (CSF) identificati nella letteratura e organizzati in principi e pilastri concettuali. Per valutarne la solidità e l'applicabilità, è stato adottato un approccio di ricerca qualitativo, fondato sull'analisi di sette case study raccolti tramite interviste semi-strutturate a professionisti direttamente coinvolti in progetti di AI lungo la supply chain.

L'analisi empirica ha seguito un approccio in due fasi, combinando within-case analysis e cross-case analysis, al fine di individuare pattern ricorrenti e differenze significative tra i casi. I risultati mostrano una forte aderenza empirica al framework, confermando la rilevanza di diversi principi come fattori abilitanti chiave per il successo dei progetti di AI. I principi applicati in modo non coerente risultano spesso associati a inefficienze o difficoltà di implementazione, fornendo ulteriore supporto alla validità del framework.

Sono inoltre emerse due principali deviazioni rispetto alla formulazione originale del framework. In primo luogo, il pilastro "Explainable and Transparent AI" non è stato adottato in modo significativo nei casi analizzati, portando a una sua reinterpretazione come elemento facilitatore piuttosto che abilitante. In secondo luogo, i risultati suggeriscono una revisione della timeline progettuale, collocando la creazione di team interdisciplinari in una fase antecedente alla valutazione delle risorse.

Nel complesso, questa tesi fornisce un contributo empiricamente fondato alla comprensione dell'implementazione dell'AI nella supply chain, offrendo sia un affinamento dei framework teorici esistenti sia indicazioni pratiche concrete. Dal punto di vista accademico, lo studio rafforza il collegamento tra teoria ed evidenza empirica, contribuendo al dibattito sui fattori critici di successo dei progetti di AI. Dal punto di vista manageriale, i risultati forniscono linee guida operative utili a manager e decision-maker per strutturare, gestire e implementare con successo iniziative di intelligenza artificiale in contesti complessi di supply chain.

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1 Introduction

1.1 Thesis Structure and Objective

In recent years, the structure and management of supply chains have become topics of increasing relevance, mainly due to the growing complexity of logistics and production systems and the competitive environment in which companies operate [1]. This complexity is further amplified by factors such as demand volatility, market globalization, and the increasing interdependence among supply chain actors.

Within this scenario, a progressive increase in interest in digital transformation paths and in the transition toward Industry 4.0 paradigms can be observed [2] which are considered key tools for addressing greater market dynamism, rising stakeholder expectations, and the constant need to optimize and improve business processes.

In this context, artificial intelligence (AI) has assumed a central role, attracting growing attention due to the opportunities it can generate within organizations. In environments characterized by increasing complexity, demand uncertainty, and growing sustainability pressures, companies are increasingly inclined to integrate AI-based solutions in order to improve operational efficiency, reduce costs, and optimize workflows.

Despite these potential benefits, not all companies consider themselves adequately prepared to undertake a change process oriented toward the implementation of artificial intelligence. The main barriers are attributable to structural and financial constraints, as well as to an organizational maturity level that is not always sufficient [3] ,in addition to the uncertainty related to project success and return on investment in AI initiatives.

In response to the growing interest in Industry 4.0 and artificial intelligence, the scientific literature has begun to develop numerous contributions aimed at identifying the critical success factors in the implementation of AI projects, as well as the main challenges that may lead to their failure.

To this end, a theoretical framework has been proposed that identifies a set of key phases and dimensions to be considered in artificial intelligence projects, with the aim of supporting their management and implementation. This thesis aim to validate and, where necessary, revise the results of this framework through the analysis of case studies, comparing the theoretical approach with the practices actually adopted by managers in the development of real projects, in order to highlight the impact and implications of any discrepancies.

This thesis contributes to both the academic literature and managerial practice by generating value on two complementary levels: the applied-managerial level and the scientific-academic level.

From a managerial perspective, the thesis provides a significant contribution by addressing the main critical issues encountered in the adoption of artificial intelligence within supply chains. Through the analysis of real case studies and their comparison with an existing theoretical framework, the study highlights which phases, competencies, and organizational conditions are truly decisive for the success of AI projects. In this way, the thesis offers managers a decision-support tool to guide planning, change management, and implementation processes, thereby reducing uncertainty and the risk of project failure.

From an academic and research perspective, the value of the thesis lies in the empirical validation of a theoretical framework through evidence drawn from real-world contexts. The systematic comparison between the conceptual model and the ways in which artificial intelligence projects are developed by managers allows for the identification of potential discrepancies, confirmations, or extensions of existing theory. In this sense, the research contributes to enriching the scientific debate on critical success factors in AI adoption, providing insights for refining theoretical models and facilitate development of further comparative or quantitative studies on the topic.

1.2 Literature Review and Implementation Framework

1.2.1 Digitalization of the Supply Chain and Challenges of AI Projects

As highlighted in [2], the concept of a digital supply chain can be defined as "*the development of information systems and the adoption of innovative technologies aimed at strengthening the integration and agility of the supply chain, thereby improving customer service and the sustainable performance of the organization*." This definition emphasizes how the digital transformation of the supply chain is not limited to the mere introduction of new technologies, but rather entails a comprehensive rethinking of information systems, processes, and integration mechanisms across the entire supply chain. In particular, the focus on agility and integration underlines the need to respond rapidly and in a coordinated manner to a competitive environment characterized by increasing complexity, demand volatility, and growing sustainability pressures.

It is precisely within this context that the continuous search for increasingly advanced, innovative, and effective technologies has contributed to creating favourable conditions for the diffusion of artificial intelligence projects within organizations [4].

AI is increasingly regarded as a strategic lever capable of supporting the evolution of the digital supply chain [5] by enhancing analytical, forecasting, and decision-support capabilities, in line with objectives related to operational efficiency and overall performance improvement.

According to a global survey conducted by Gartner in June 2024 [6] with 419 supply chain leaders, artificial intelligence (AI), including machine learning, and generative AI (GenAI) are the top digital supply chain investment priorities(Figure1.1). The results indicate that a significant portion of respondents considers these technologies crucial for driving digital transformation, improving operational efficiency, and supporting faster, data-driven decision-making. This highlights that AI is perceived not only as a technical tool but also as a strategic lever to strengthen organizational competitiveness on a global scale.

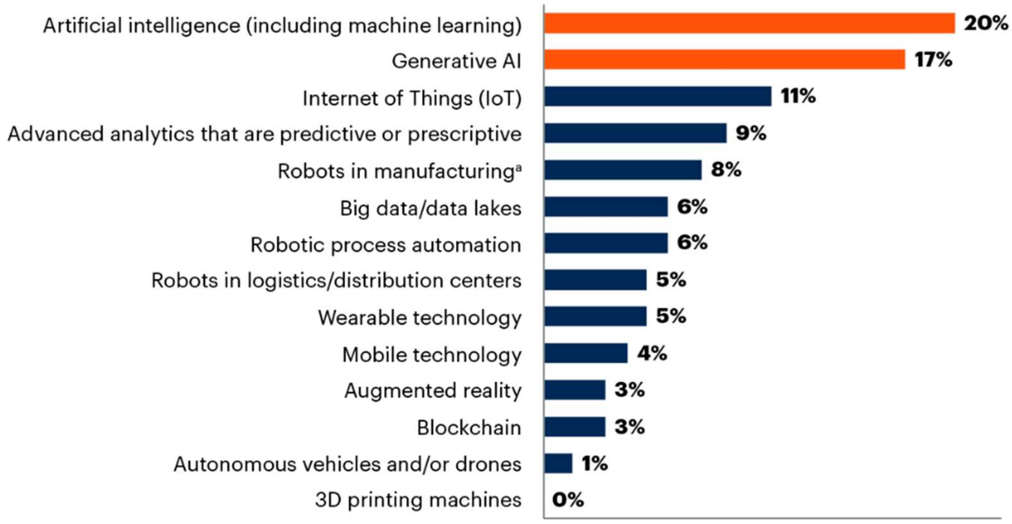


Figure 1.1 Gartner survey : investment priorities [6]

However, the survey reveals significant differences across regions, roles, and industries. In Western Europe, for example, AI is given relatively lower priority compared to other regions, as companies tend to focus investments on technologies aligned with Industry 4.0 objectives, such as robotics and smart manufacturing. This suggests that while AI remains relevant, its adoption is shaped by the industrial context and local strategic priorities.

Nonetheless, global interest in AI and GenAI remains high, confirming that these technologies are viewed as key enablers of digital transformation and sustainable competitive advantage in the medium to long term.

Finally, Gartner emphasizes that prioritizing AI strategically requires aligning investments, skills, and technology roadmaps to ensure organizations can fully exploit the potential of these technologies, rather than relying on isolated implementations or short-term gains.

However, despite the strong theoretical potential and the high level of interest shown by companies, the literature highlights that the implementation of artificial intelligence is often associated with results that fall short of expectations. In particular, Mohammad I. Merhi in *An evaluation of the critical success factors impacting artificial intelligence implementation* [7] points out that only a limited percentage of AI projects manage to complete the entire development cycle and reach the production stage. This evidence highlights the existence of a significant gap between the strategic interest in AI and organizations' ability to translate such interest into operational and scalable solutions.

The adoption and implementation of artificial intelligence can in fact be described as a highly complex process, characterized by substantial time and resource requirements. These projects demand not only significant financial investments, but also the availability of adequate structural and human resources. Moreover, AI implementation typically involves multiple organizational functions, requiring a high level of coordination and strong integration among technical, managerial, and operational competencies. This complexity helps explain why many initiatives fail to move beyond the experimental phase or encounter difficulties in transitioning to stable and continuous use.

Within this context, several studies have focused on analysing the factors influencing so-called "AI readiness," defined as the degree to which an organization is prepared to successfully adopt and implement artificial intelligence solutions. According to Wajid Ali and Abdul Zahid Khan [8] one of the most relevant elements is the quality and maturity of the IT infrastructure, which represents a fundamental prerequisite for the development and integration of AI systems. This factor is accompanied by top management support, the availability of financial resources, the presence of a flexible and innovation-oriented organizational culture, and the organization's ability to effectively manage change. Another critical element concerns data quality, availability, and governance, which are considered essential prerequisites for the effective functioning of AI solutions.

Empirical evidence reported by McKinsey in "*Succeeding in the AI supply-chain revolution*" [1] is consistent with these considerations. In particular, the study highlights that more than 60% of AI projects applied to the supply chain tend to exceed initial timelines and cost estimates, confirming the difficulty of managing such initiatives effectively. McKinsey attributes these challenges to a set of recurring factors, including limited clarity regarding the actual value generated by the project, difficulties in defining objectives and selecting appropriate technological solutions, and the complexity of vendor selection processes. These issues are further compounded by a lack of prior experience in implementing and integrating large-scale projects, challenges related to change management, and shortages of specific skills required to use and manage artificial intelligence systems.

Finally, *"Exploring AI adoption in manufacturing: An empirical study on effects of AI readiness"* [3] shows that companies that have successfully implemented AI and digitalization initiatives have placed strong emphasis on the management of human resources and intangible assets. In particular, these organizations have invested in fostering an innovation-friendly corporate culture, continuous employee training, and the enhancement of flexibility and adaptability to technological change. The study highlights that these elements, when supported by adequate infrastructural readiness, significantly contribute to increasing overall AI readiness and improving the likelihood of success of artificial intelligence projects.

According to *Teixeira, A.R.; Ferreira, J.V.; Ramos, A.L.* [9] the adoption of artificial intelligence (AI) and machine learning (ML) in supply chain management represents one of the most promising opportunities for enhancing operational efficiency, resilience, and decision-making capabilities within organizations. However, despite its transformative potential, numerous studies have highlighted that the full implementation of these technologies is hindered by a multitude of complex challenges, which can be categorized as technological, organizational, economic, ethical, and cultural.

Among the key technological challenges, data quality and availability represent critical barriers. Incomplete, inconsistent, or fragmented data significantly reduce the reliability of AI/ML models and limit their predictive accuracy, particularly in risk management systems and demand forecasting applications. This issue is further compounded by the reluctance of suppliers and supply chain partners to share sensitive information, which restricts the adoption of centralized and collaborative AI solutions. Additionally, integration with legacy systems remains a major obstacle, as many traditional enterprise platforms were not designed to interface with advanced AI models, often necessitating costly and complex migration or adaptation processes.

Model scalability is another significant challenge. Many AI initiatives remain at a pilot or experimental stage and require continuous adaptation and validation to function effectively in real-world operational contexts, where conditions are more variable and unpredictable. Performance variation among different models underscores the importance of careful selection of inputs, parameters, and algorithmic approaches. The lack of model explainability (black-box models) further reduces trust and perceived reliability among decision-makers, prompting the development of explainable AI frameworks to enhance transparency and interpretability in automated decision-making systems.

Organizational and cultural barriers are equally critical. Resistance to change and automation, combined with a lack of specialized internal skills, limits the ability of companies to implement AI solutions effectively and sustainably. Successful adoption requires not only technical expertise in data science and machine learning but also a deep understanding of supply chain processes, continuous employee training, and the creation of interdisciplinary teams. The absence of structured AI governance and clear strategic roadmaps reduces the ability to coordinate investments and monitor the long-term impact of AI initiatives. Moreover, multi-actor collaboration and disparities in data access among partners present further obstacles to the seamless implementation of integrated AI-driven solutions.

Economic barriers are also significant. High implementation costs, including expenses for software, hardware, cloud platforms, personnel training, and system maintenance, along with uncertainty regarding return on investment (ROI), may discourage companies, especially small and medium-sized enterprises, from investing in AI. Even in advanced contexts, such as autonomous robotics or AI-driven supply chain finance systems, the perceived value relative to the cost can be unclear, limiting adoption and technology diffusion.

Ethical and legal considerations pose additional challenges. Issues related to data privacy, algorithmic bias, and automated surveillance generate concerns among both managers and external stakeholders. Lack of trust in AI outcomes, exposure to cybersecurity risks, and regulatory uncertainties require organizations to develop responsible adoption strategies to ensure fairness, transparency, and security in AI-driven decision-making processes.

Other critical factors concern the management and continuous maintenance of AI models. AI adoption requires regular model updates, periodic validation of results, and the capacity to select appropriate algorithms for specific supply chain functions, such as demand forecasting, warehouse optimization, or supplier management. Advanced approaches, such as federated learning, may be limited by disparities in data access and reluctance to share information among partners, further increasing operational complexity.

In summary, effective implementation of AI and ML in supply chain management requires a holistic, multidimensional approach that combines technological investment, skills development, governance frameworks, continuous model adaptation, change management, and attention to ethical and legal considerations. Only through an integrated strategy, balancing technological, economic, and cultural needs, can organizations fully leverage AI's transformative potential, enhancing operational efficiency, resilience, decision-making, and long-term competitiveness.

Overall, the evidence emerging from the literature shows that success in implementing AI within the supply chain does not depend solely on the availability of advanced technologies, but rather requires a systemic approach that integrates technological, organizational, and cultural dimensions. This awareness represents a key element for understanding the difficulties faced by companies and constitutes the starting point for the analysis proposed in this thesis.

1.2.2 Initial Framework and Design Pillars for the Implementation of AI Projects in the Supply Chain

The theoretical framework underlying this thesis represented in *"What could go wrong?" Unlocking AI Potential in Supply Chain Management: Design Principles and Best Practices* [10] is designed to support and guide management throughout the complex process of implementing artificial intelligence within the supply chain. Specifically, the framework is conceived as a decision-support tool that provides a structured and systemic view of the main phases characterizing an AI project, helping managers navigate a context marked by high technological, organizational, and strategic complexity.

In order to identify the constitutive phases of the framework, a systematic literature review was conducted by the authors with the aim of rigorously analysing the most relevant contributions in the scientific literature on artificial intelligence implementation. This review made it possible to identify and understand the factors that the literature recognizes as critical success factors (CSFs) in AI projects, with particular reference to the supply chain and logistics-production context.

Once identified, the critical success factors emerging from the literature were analysed, compared, and synthesized in order to reduce fragmentation and overcome the heterogeneity of approaches found across different studies. Subsequently, these factors were grouped and reorganized coherently, with the aim of building a logical and sequential structure capable of reflecting the different phases of the artificial intelligence project life cycle. This systematization process made it possible to transform a heterogeneous set of theoretical insights into an organic framework that is easily interpretable and applicable from a managerial perspective.

The resulting framework is therefore structured to help managers throughout the entire process of implementing an AI project in the supply chain, starting from the initial phases of ideation and definition of the initiative, moving through feasibility assessment and resource identification, and extending to the operational phases of development, deployment, and post-deployment management. In particular, the framework adopts an integrated view of the different types of resources involved in the project, including not only financial resources, but also structural, technological, and human resources, which the literature recognizes as fundamental elements for the success of artificial intelligence initiatives.

Through this approach, the framework aims to support management in understanding which factors must be considered at each stage of the project and in what sequence, thereby reducing the risk of fragmented approaches or excessive focus on isolated technological aspects. In this sense, the proposed model emphasizes the need for a holistic approach to AI implementation, in which technological decisions are aligned with the organizational, strategic, and operational dimensions of the supply chain.

Overall, the framework represents a structured synthesis of the main evidence emerging from the literature and constitutes the theoretical foundation on which the empirical analysis of this thesis is based. By comparing this framework with the practices actually adopted by organizations in the analysed case studies, the research aims to assess its validity, applicability, and effectiveness in supporting the implementation of artificial intelligence within the supply chain.

The research resulted in the identification of 32 design principles, which were subsequently grouped into 10 "Design Pillars." These pillars are described below.

Organization's Structure

This pillar refers to the numerous and significant changes that organizations must address in terms of reshaping their internal structure, defining new roles, and redefining tasks and responsibilities in order to effectively manage the innovation introduced by artificial intelligence systems. The implementation of AI solutions does not merely represent a technological upgrade; rather, it entails a comprehensive reconfiguration of organizational processes, hierarchies, decision-making chains, and workflows, with a direct impact on nearly all business functions.

AI Knowledge

The literature highlights that, before initiating an artificial intelligence implementation project, it is essential for organizations to develop an in-depth understanding of the different solutions, techniques, and approaches available. This preliminary phase aims to enable decision makers to gain awareness not only of the technological potential of AI systems, but also of how these solutions can be integrated into existing processes and contribute to the achievement of business objectives. To this end, companies should explore available market alternatives, analyse previously implemented use cases, and evaluate the experiences of other organizations in order to understand the strengths, limitations, and application areas of different solutions and identify those most suitable for their operational context.

Employees' Management

Human resources represent a central element in the functioning and success of any organization, and employees' behaviour, skills, and openness to change have a significant impact on the outcomes of innovation projects. The introduction of artificial intelligence systems affects not only operational processes but also people, as these technologies can profoundly alter working methods, automate tasks traditionally performed by humans, and redefine professional roles. In this context, employee management plays a crucial role, making it necessary to accompany employees throughout the transition process by supporting skill development and fostering understanding of the changes introduced by AI.

Stakeholders' Management

Employees directly involved in the department where the artificial intelligence system is implemented do not represent the only relevant stakeholder group. Organizations must identify and manage a broader set of stakeholders, both internal and external, involving them from the early design stages and maintaining continuous dialogue throughout the entire development and implementation lifecycle. These stakeholders include, for example, interconnected or interdependent departments, as well as other organizational functions that may be affected by the project's outcomes. In this context, clearly communicating the strategic value of the initiative is essential to ensure alignment, support, and a shared understanding of project objectives.

Organizations' Strategy

The adoption of artificial intelligence systems is recognized in the literature as a potentially decisive factor for organizational growth and competitiveness. However, organizations should not initiate AI projects solely in response to innovation pressure or technological trends. Instead, it is necessary to critically assess the tangible benefits that AI can generate and verify that its implementation is consistent with the company's long-term strategy. From this perspective, artificial intelligence should be viewed as a tool supporting business objectives and strategic vision, rather than as an end in itself.

Governance & Communication

In recent years, the definition of rules, principles, and guidelines for the use of artificial intelligence has become a topic of primary importance at the international level. A relevant example is the European Union's AI Act, approved in 2023 with the aim of establishing obligations and requirements for AI in specific application domains. Within an evolving regulatory landscape, organizations must therefore adopt appropriate governance policies designed not only to ensure compliance with existing regulations, but also to exercise responsible and informed control over the use of AI within the organization. Another important aspect concerns system communication and transparency, which can be enhanced through the adoption of explainable AI solutions capable of making results more understandable and reducing the perceived opacity of algorithmic decisions.

Data & Infrastructure

The functioning of artificial intelligence systems largely depends on the availability of adequate, reliable, and high-quality data. For this reason, organizations must be able to ensure a continuous and structured flow of data, which is an essential condition for AI solutions to generate value. Since such data primarily originate from internal systems, companies must have reached an advanced level of digitalization, possess up-to-date IT infrastructures, and have well-established capabilities in data management and integration. Furthermore, the technological architecture must be sufficiently flexible to allow the integration of new artificial intelligence systems with existing platforms.

Financial Capability

The implementation of artificial intelligence systems requires significant investments, both during the initial development phase and in subsequent implementation, management, and maintenance activities. Consequently, organizations embarking on this path must have a clear understanding of their financial resources and the economic sustainability of the project. In the absence of careful planning, the expected benefits of AI adoption may be undermined by unforeseen costs, delays, or solutions that are difficult to scale. At the same time, organizations must assess whether they possess the necessary internal competencies to manage projects of such complexity or whether it is more appropriate to rely on specialized external providers.

Top Management

Innovation projects require strong leadership and clear direction in order to be successfully implemented. Given the complexity and uncertainty associated with the introduction of artificial intelligence systems, active involvement of top management is a critical element. Senior executives must be aware of the strategic implications of the project and support its development by ensuring the availability of resources, continuity, and organizational legitimacy. In the absence of such support, AI projects risk being downsized or discontinued. Moreover, the project leader must possess adequate competencies and act as a promoter of the initiative, guiding the organization within a context characterized by high decision-making complexity.

Post-Deployment

The post-deployment phase is only marginally addressed in the literature, yet it plays a crucial role in assessing the long-term success of artificial intelligence projects. Once the system has been implemented, it becomes necessary to define clear criteria and metrics to evaluate whether adoption has produced the expected results and whether the value generated is consistent with the initial objectives. At the same time, organizations must continuously monitor system performance to ensure stable operation over time and to intervene promptly in the event of deviations from predefined standards or expectations.

Table 1.1 Framework pillars and principles

PILLAR	PRINCIPLES			
ORGANIZATION'S STRUCTURE	Adapt organization's structure	New tasks and roles	Assign responsibilities	
AI KNOWLEDGE	Existing AI solutions and cases	AI solutions' potential	Prioritize AI solutions	
EMPLOYEES' MANAGEMENT	Employees' skills and knowledge	Train employees	Mindset and propensity to change	Reassure employees
STAKEHOLDERS' MANAGEMENT	Identify and involve stakeholders	Create interdisciplinary teams	Effective and transparent communication	Clear department importance
ORGANIZATION'S STRATEGY	Benefits of AI adoption	Alignment of AI with business objectives	Alignment of AI with the strategic plan	
GOVERNANCE & COMMUNICATION	Governance rules and data management	Data privacy and security	Explainable and transparent AI	
DATA & INFRASTRUCTURE	Appropriate IT system	AI integration	Data quality and quantity	
FINANCIAL CAPABILITY	Resource assessment	Outsourcing vs. internal development	Suppliers' evaluation	
TOP MANAGEMENT	Top management support	Define a project champion	PM leadership and mindset	
POST-DEPLOYMENT	Define KPIs	Monitor system operativeness	Implement corrective actions	

Organization's Structure

Adapt organization's structure: The first principle concerns the need to ensure that the organizational structure and process design are optimally aligned to support the successful implementation of AI. At this stage, the organization must first clarify whether the adoption of AI systems is part of a broader digitalization or technological innovation plan, determining whether it is necessary to establish a dedicated internal department to coordinate the initiative. This analysis requires an in-depth evaluation of the internal structure, with the possibility of revising the organizational chart, redesigning hierarchical lines, and creating new functions specifically dedicated to the management and monitoring of AI systems. At the same time, it is essential to analyze and map existing business processes to understand their interactions, dependencies, and critical integration points. The process adaptation phase involves targeted modifications that enable seamless integration between new AI technologies and established operational practices, reducing the risk of misalignment or inefficiencies. This approach ensures that the introduction of AI does not disrupt operational continuity and maximizes the value generated by the new system.

New tasks and roles: The second principle concerns the definition of new tasks and role profiles. The introduction of AI systems requires updating existing job descriptions and developing new professional roles specifically designed to interact with intelligent systems, analyse their outputs, and support their maintenance. Organizations must identify the key competencies required for these new roles and assess whether such skills are available internally. If not, they must decide whether to hire new qualified personnel or invest in training existing employees. Once the roles are identified, it is essential to clearly define the daily activities associated with each profile, clarifying operational responsibilities and ensuring that each individual understands their contribution to the functioning of the AI system. This phase not only improves process efficiency but also facilitates employee acceptance of change, reducing resistance and uncertainty.

Assign responsibilities: The third principle concerns the clear assignment of responsibilities. AI systems, especially those involved in decision-making processes, require organizations to maintain high levels of accountability and transparency. Therefore, it is essential to define who is responsible for monitoring system decisions, verifying their reliability, and intervening in the event of anomalies or deviations from expected outcomes. Responsibilities must be established both during the project implementation phase and after system deployment, ensuring the presence of dedicated figures for continuous supervision. This implies the creation of detailed documentation, such as the project charter, project specifications, and AI system operating manuals, to ensure clarity and traceability. In particular, it is necessary to define: the roles responsible for project development and implementation; the organizational roles authorized to access and interact with the system; those responsible for maintenance and operational management; and finally, the individuals in charge of analysing AI-generated outputs and making decisions based on them. This level of clarity significantly reduces the risk of inefficiencies, decision-making errors, or overlapping responsibilities, facilitating a safer and more sustainable adoption of AI over time.

AI Knowledge

Existing AI solutions and cases: At this stage, the organization must develop in-depth knowledge of artificial intelligence and identify concrete use cases that are feasible, implementable within reasonable timeframes, and capable of generating measurable business value. It is essential to map AI applications already adopted in similar contexts, analysing how other companies have addressed comparable challenges, which technological approaches they used, and what concrete results were achieved. Organizations can participate in AI-focused conferences, workshops, and seminars, observing successful examples and critically analysing the strategies adopted by other players. Another important channel for knowledge development is the involvement of external AI experts who can share expertise and insights on algorithms, architectures, and best practices.

AI solutions' potential: Once potential solutions have been identified, their impact on the business and their alignment with organizational objectives must be assessed. This evaluation involves analysing the effects of the solution on operational processes, decision quality, resource efficiency, and overall economic performance. The assessment of solution potential is not limited to technical aspects but also considers the organization's ability to adopt, manage, and integrate the AI system into existing processes, anticipating potential operational challenges or organizational adaptation needs.

Prioritize AI solutions: Finally, the organization must analyse and rank the identified solutions to define priorities based on their potential impact and implementation feasibility. At this stage, it is important to consider both estimated economic benefits and the probability of project success, assessing risks, integration complexity, and human and technological resource requirements. Prioritization allows organizations to select solutions that offer the best balance between generated value and acceptable risk, ensuring a structured and strategic approach to choosing the most suitable AI solution. This evaluation and selection process should be clearly and systematically documented, creating a decision map that guides managers during subsequent implementation phases, reducing uncertainty and facilitating alignment between strategic objectives and expected operational outcomes. Overall, the development of AI knowledge represents a fundamental prerequisite for project success, as it enables organizations to make informed choices, properly plan implementation phases, and reduce the risk of errors or inefficiencies. Only through an adequate understanding of available solutions, their potential impact, and their feasibility can organizations create the conditions for effective AI adoption, maximizing business value and ensuring long-term project sustainability.

Employees' Management

Employees' skills and knowledge: To successfully develop and implement AI projects, it is essential to have employees with adequate skills, not only for system development but also for operational use, maintenance, and continuous performance monitoring. Consequently, assessing the current level of skills and knowledge within the organization is crucial. Organizations can promote group meetings, workshops, and discussion sessions with employees to understand their familiarity with AI technologies and identify skill gaps that could jeopardize project success.

Train employees: Ensuring adequate employee training is a critical element in maximizing the potential of AI solutions, enabling proper model selection, effective system use, and continuous performance monitoring. Organizations must define and develop targeted training programs designed to bridge the gap between employees' current knowledge levels and those required by the AI project. Training paths should be tailored to different organizational roles and focused on topics relevant to specific responsibilities, strengthening the organization's ability to fully leverage the implemented systems.

Mindset and propensity to change: Another critical aspect concerns employees' willingness to actively participate in AI projects and their propensity to accept technological change. Understanding employees' perceptions, expectations, and concerns is essential to ensuring their collaboration, which is a key factor for project success. Organizations should collect and analyse employee opinions using a structured approach such as interviews, focus groups, or one-on-one meetings. Actively involving both directly and indirectly affected employees helps identify resistance, fears, or perceived issues, fostering transparency and participation.

Reassure employees: One of the main obstacles to AI acceptance is fear of job changes or job loss. Therefore, organizations must adopt targeted strategies to reassure employees and orient their mindset toward openness and acceptance of change. Once key concerns are understood, management should guide employees through an acceptance process by organizing learning opportunities to reduce knowledge barriers and providing opportunities for hands-on experimentation. For example, allowing employees to test similar systems or prototypes before full implementation can increase familiarity and reduce uncertainty. This approach helps create a climate of trust and collaboration, increasing the likelihood of successful AI implementation. Overall, effective human resource management is essential for AI project success, as it aligns employee skills, attitudes, and behaviours with organizational strategic objectives, reducing resistance and fostering sustainable long-term adoption.

Stakeholders' Management

Identify and involve stakeholders: The first step is the systematic identification of relevant internal and external stakeholders and their involvement from the project design phase. During planning, organizations should dedicate time and resources to stakeholder mapping, listing them and analysing the role each can play in project development and success. This process helps assess stakeholders' influence, interest, and impact, enabling the definition of mitigation actions to reduce the risk of opposition. At the same time, stakeholders who can actively contribute to successful implementation should be proactively involved. It is also essential to define appropriate communication methods for each stakeholder category, considering their specific information needs and level of involvement.

Create interdisciplinary teams: To effectively cover the diverse areas of expertise required by AI projects, creating interdisciplinary teams is considered a best practice. This involves defining a project team that includes all key figures and ensures the right people are involved at the appropriate stages. Engaging stakeholders from different organizational functions integrates diverse perspectives, ensuring a comprehensive view of technological, operational, organizational, and strategic aspects. Heterogeneous competencies foster idea generation, innovative solutions, and improved anticipation of potential issues, enriching the project overall.

Effective and transparent communication: Structured, clear, and transparent communication is crucial to reducing information gaps and stakeholder resistance while strengthening trust and commitment. Organizations should define specific communication methods for all stakeholders, recognizing that no one-size-fits-all approach exists. Different stakeholder categories require tailored content, frequency, and communication tools. Communication may occur via emails, periodic meetings, workshops, or dedicated sessions. Moreover, when stakeholders request information, and where confidentiality policies allow, providing project updates can help resolve obstacles or offer new perspectives useful for project development.

Clear department importance: To ensure effective AI implementation within a specific department, it is essential that the value contribution of that organizational unit is clearly understood by all stakeholders. During initial meetings, the strategic importance of the department where AI will be implemented should be explicitly communicated, clarifying project motivations. This can be achieved by describing current processes, key issues, and operational limitations, while also presenting a clear vision of potential benefits. Highlighting not only organizational-wide advantages but also the specific impact on individual stakeholders fosters understanding, acceptance, and support. Overall, structured and proactive stakeholder management is a critical success factor for AI projects, as it aligns interests, expectations, and contributions. An inclusive and transparent approach reduces resistance, improves decision quality, and increases the likelihood of effective and sustainable implementation.

Organization's Strategy

Benefits of AI adoption: It is essential to reach early consensus on objectives and expected benefits from AI adoption. During project planning, organizations should clearly define intended outcomes, both operational and strategic, such as efficiency improvements, cost reductions, service quality enhancement, or improved decision-making capabilities. To ensure accurate and realistic evaluation, individuals with technological expertise should be involved to provide a reliable understanding of AI's potential benefits and limitations.

Alignment of AI with business objectives: AI implementation must be consistent with organizational goals and its propensity for change and digital transformation. Assessing the company's digital maturity and management's willingness to engage in transformation is essential to ensuring project support. AI adoption often requires changes in processes, decision-making approaches, and skills, making it crucial to verify organizational readiness to accept such changes and invest in necessary resources.

Alignment of AI with the strategic plan: A clear and strong connection between organizational vision and strategy must be established so that AI adoption contributes concretely to business objectives. Organizations should analyse their identity, mission, and core values to ensure consistency with AI project goals. Strong strategic alignment helps avoid isolated initiatives disconnected from core business and increases the likelihood of long-term value creation.

Governance & Communication

Governance rules and data management: AI governance policies must be defined to ensure responsible implementation, addressing key issues such as ethics, integrity, fairness, and justice. Initially, organizations should verify compliance with local and international regulations. Subsequently, establishing a dedicated AI governance team can help assess ethical and legal implications, discuss emerging issues, and propose risk-mitigation solutions, increasing project success probability.

Data privacy and security: AI applications require particular attention to data protection and information security. Organizations must ensure compliance with privacy and security regulations and clearly define which data can be used for algorithm training and operation. It is also necessary to determine whether systems can access external data sources and manage risks associated with inaccurate or uncontrolled external data. Adequate protection of sensitive data and restriction of unauthorized access are therefore essential.

Explainable and transparent AI: Developing explainable and transparent AI systems is key to fostering acceptance and effective use. Algorithms should not be perceived as "black boxes" but should allow users to understand underlying decision-making processes. This can be achieved through outputs highlighting critical decision factors or by integrating tools such as chatbots or explanatory interfaces. Greater transparency improves user trust and facilitates organizational control and accountability.

Data & Infrastructure

Appropriate IT system: AI requires a robust technological infrastructure. Organizations must assess the current state of IT systems and verify the availability of required resources. This involves mapping existing information systems, analysing their interoperability, and ensuring AI-required information is accessible. Where gaps exist, systems must be developed or updated to ensure data availability and technological compatibility.

AI integration: AI systems operate closely with other organizational information systems, making integration a critical implementation aspect. Ensuring proper connection with existing IT infrastructure allows continuous, coherent, and uninterrupted data flows. Ineffective integration can compromise AI performance and significantly reduce generated value, requiring careful interface and data-exchange design.

Data quality and quantity: Data quantity and quality are fundamental prerequisites for AI system performance. Data must be accurate, complete, consistent, and up to date, requiring structured cleaning, preparation, and management processes. Organizations must ensure sufficient data volume and adequate quality standards by defining robust data management and governance processes.

Financial Capability

Resource assessment: AI projects require significant financial investment, making it essential to assess the organization's ability to sustain the initiative in the medium to long term. This phase involves defining a dedicated budget and realistically estimating total costs, including development, integration, training, maintenance, and updates. Human resources and internal competencies are also critical; organizations must ensure sufficient qualified personnel availability.

Outsourcing vs. internal development: Organizations must evaluate strategic options for AI development: internal, fully outsourced, or hybrid models. If AI is considered a core strategic component, internal development may be preferred, allowing greater flexibility, control, and ownership. Full outsourcing can be faster and less demanding in terms of internal expertise but reduces autonomy. Hybrid approaches combine internal development with external partnerships where specific resources are lacking.

Suppliers' evaluation: When outsourcing AI development, vendor selection becomes a critical success factor. Organizations must carefully evaluate providers based on criteria such as cost, solution quality, experience, timelines, and ongoing support capability. Market analysis can include trade fairs, vendor comparisons, demos, and case studies.

Top Management

Top management support: Top management support is one of the main enablers of AI projects, helping overcome internal resistance and ensuring resource allocation. Involving top management from early stages and securing strategic backing is essential. Executive sponsorship can also provide decision support and additional resources during critical project phases.

Define a project champion: Given AI project complexity, having a project champion with specific expertise is essential to address technical and organizational challenges.

Responsibility should be assigned to an experienced individual capable of leading the team, solving complex problems, and maintaining focus on objectives.

PM leadership and mindset: Strong leadership is essential to keep the project under control and aligned with objectives. AI project managers must have a digital and innovation-oriented mindset, openness to change, and strong leadership skills to manage complexity, handle opposition, and maintain alignment.

Post-Deployment

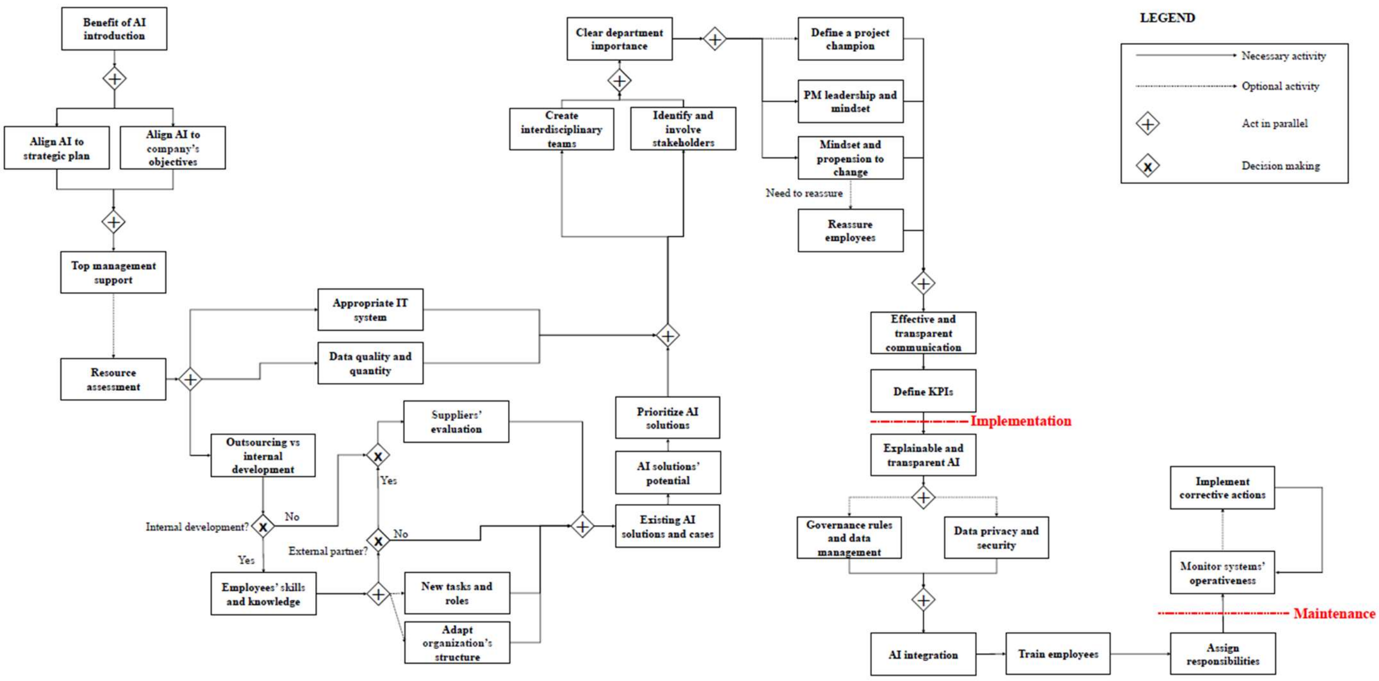
Define KPIs: Key performance indicators (KPIs) must be defined to evaluate AI system effectiveness and compare performance with benchmarks. These metrics help determine project success and alignment with objectives and should be realistic and progressively refined.

Monitor system operativeness: After implementation, AI systems must be continuously monitored to detect performance variations. Ongoing benchmark comparisons help ensure reliability and robustness over time.

Implement corrective actions: If performance declines, timely corrective actions are required. Maintenance activities should be planned from the outset, enabling organizations to restore desired performance levels and preserve investment value.

Once the research authors grouped the various principles and identified the fundamental pillars for AI project development in the supply chain, these elements were mapped and organized into a theoretical framework designed to support project implementation. The resulting framework represents the conceptual starting point of this thesis. As anticipated, the objective of this work is to validate and, where necessary, revise the proposed framework through an empirical approach based on case study analysis and interviews with managers from different companies. These managers shared their concrete experiences related to the management and implementation of AI projects in the supply chain, enabling a direct comparison between the theoretical model and real-world practices.

Figure 1.2 Theoretical framework



2 Research Methodology

2.1 Project Selection Process and Criteria

To analyse the barriers to the adoption of artificial intelligence in supply chain contexts, this study adopts a multiple case study approach. The case selection process did not start from the direct identification of specific AI projects but from a preliminary phase aimed at identifying organizations that had explicitly undertaken structured digitalization initiatives. This choice is based on the assumption that a higher level of digital maturity increases the likelihood of finding individuals with direct experience in AI projects, particularly those applied to supply chain processes.

Once this initial set of companies was identified, the analysis focused on verifying the actual presence of AI initiatives consistent with the research objectives. Particular attention was also given to industrial sectors where artificial intelligence is expected to have a significant impact on supply chain processes, such as manufacturing, logistics, and contexts characterized by complex, information-intensive operations. Focusing on these areas further facilitated the identification of relevant projects and well-informed respondents, making the data collection process more effective.

Following this exploratory phase, the final case selection was based on the coherence of the projects with the analysis context, including only AI initiatives applied to supply chain processes such as procurement, demand forecasting, production planning, inventory management, logistics, Industry 4.0, and manufacturing. To identify projects suitable for analysis, a systematic process was established to find potential candidates for interviews. The first phase relied on desk research, including targeted online searches and the use of the professional network LinkedIn, aiming to identify professionals with job titles most likely exposed to the development, management, or coordination of AI projects within the supply chain. Examples include roles related to digital transformation, advanced analytics, supply chain management, operations management, and IT strategy.

Once potential interviewees were identified, they were contacted directly to gather preliminary information regarding the types of projects they had participated in, their role within these initiatives, and the organizational context in which the projects were developed. This preliminary screening phase aimed to verify the alignment of the described projects with the research criteria, particularly the presence of AI solutions applied to supply chain processes and the comparability of initiatives in terms of objectives, complexity, and organizational impact.

If projects were deemed consistent with the selection criteria, candidates were considered eligible for the interview and included in the analysis sample. This approach allowed for a progressively refined case selection, reducing the risk of including irrelevant experiences and ensuring a high level of consistency among the analysed projects. Moreover, the direct involvement of respondents during the screening phase enabled the collection of more accurate and contextualized information, improving the overall quality of the qualitative data used in the study. Particular attention was also paid to the comparability of projects, considering factors such as the application area, pursued objectives, and organizational impact, to enable meaningful cross-case analysis.

Although these projects were developed within organizations operating in different sectors and markets, company characteristics do not constitute the primary unit of analysis. Instead, they are considered as contextual elements, while the main focus of the research is on the individual AI projects. This approach allows abstraction from the specifics of each company and emphasizes the barriers emerging in the implementation process of comparable AI initiatives within the supply chain.

The evidence collected is subsequently used to compare different project experiences, identify recurring patterns and common criticalities, and derive general insights into the barriers hindering the adoption of artificial intelligence in supply chain projects. The following tables (Table 2.1) summarize the main characteristics of the selected cases. For confidentiality reasons, references to companies and projects have been anonymized, and the information presented focuses on structural and organizational aspects relevant to the research objectives.

ALIAS	N° of Employees	Sector	Project Scope
ALPHA	20.000-40.000	Cable Manufacturing	Shop floor safety; Machinery configuration forecasting
BETA	2000-5000	Semiconductors	Quality control
GAMMA	2000-5000	electrical and electronic components	Component Identification for Assembly
DELTA	10.000-20.000	Healthcare	Demand Forecasting and Minimum Stock Level

EPSILON	200.000	Automotive	Predictive Maintenance
ZETA	10-15	Fastners	Quality Control

Table 2.1 Project context

For the selection of interviewees, a minimum of three years of experience in managerial roles was adopted as the main criterion (Table2.2). This choice was made in order to ensure an adequate level of seniority and decision-making responsibility, thereby increasing the likelihood that participants had developed a broad and structured understanding of organizational processes and business dynamics. Several years of managerial experience, in fact, make it more likely that individuals have been involved in multiple initiatives, often characterized by different levels of complexity and organizational impact.

In particular, this requirement was considered relevant to increase the probability that interviewees had direct or indirect experience with digital transformation initiatives and with the implementation of artificial intelligence solutions within the supply chain. Participation in multiple projects throughout one's career also enables the development of greater awareness of recurring challenges, organizational and technological barriers, as well as of the enabling factors that influence the success or failure of such initiatives. Consequently, the selection of profiles with at least three years of managerial experience contributed to the collection of richer and more articulated qualitative evidence, grounded in concrete experiences and in-depth understanding of decision-making processes, thereby strengthening the robustness and reliability of the analyses developed in this thesis.

Table 2.2 Description of interviewees

ALIAS	Job Title	Years of experience
ALPHA	Digital Innovation Lead	6 years
BETA	Artificial Intelligence & RPA Team Manager; Automatic optical inspection engineer	10 years; 6 years
GAMMA	Group Head of Production Engineering & Digital Mfg	20-25 years
DELTA	Global Supply Chain Planning Associate Director	10-15 years
EPSILON	Project Quality Manager	5 years
ZETA	CEO	20 years

The solutions that were initiated, designed, and subsequently developed by the companies involved in the study are described in detail as following:

Case A(company ALPHA): The project focuses on the use of machine learning software to identify the optimal operating parameters of production line machinery. The main objective is to leverage the large volume of historical data generated by process instrumentation in order to analyze, understand, and optimize the performance of the production system.

By applying machine learning techniques, the project aims to identify machinery configurations that maximize process performance, enabling the achievement of target values for production specifications considered strategic within the reference market. In this way, the proposed solution supports data-driven decision-making, enhances process control, and contributes to improving the overall competitiveness of the industrial system.

Case B(company ALPHA): The project focuses on the implementation of a solution aimed at improving safety within production departments. The primary objective is to identify and analyse near-miss events occurring during operators' activities, with the goal of optimizing production processes, reducing the risk of workplace accidents, and enhancing operational efficiency by minimizing delays caused by such events.

To this end, a machine vision system has been developed and deployed within the production environment, capable of automatically detecting key elements of interest, such as operators, forklifts, designated safety areas, and other objects potentially involved in hazardous situations. The system also analyzes the dynamic state of these elements, considering parameters such as movement trajectories and speed, and enables the identification and prediction of near-miss situations, thereby providing effective support for accident prevention and continuous safety improvement.

Case C(company BETHA): initiated a project aimed at integrating artificial intelligence and machine learning into quality control processes, applying computer vision and deep learning solutions. The main objective was to improve efficiency and reliability in detecting potential defects, reduce waste, and optimize resource utilization. The initiative was driven by the need to enhance production quality in an increasingly demanding market, contain operational costs, increase productivity, and optimize overall business processes.

Case D(company GAMMA): developed a project based on machine vision and deep learning technologies applied to quality control processes, born from the need to improve efficiency and reliability in the assembly of electronic components. The project's main goal was to create an intelligent system capable of supporting and guiding operators in selecting the correct components, reducing errors and waste during manual assembly of electronic devices. This approach allowed for optimization of the entire production process, improving the final product quality, increasing overall productivity, ensuring greater standardization of operational procedures, and better management of both human and material resources involved.

Case E(company DELTA): implemented a simulation tool based on machine learning predictive algorithms to support inventory control and management. Specifically, the tool was designed to identify the minimum stock level required to maintain customer service levels. The main objectives of the initiative were to reduce warehouse costs, preserve the company's competitiveness, and free operators from low-value tasks, allowing them to focus on process innovation and improvement activities.

Case F(company EPSILON): implemented a predictive maintenance algorithm aimed at eliminating repetitive and inefficient manual tasks that previously caused frequent production interruptions. Maintenance had originally been performed reactively, when products systematically fell outside the expected technical tolerances. The project's objective was therefore to anticipate such issues, proactively plan maintenance interventions, reduce manual inspection times, and decrease production waste.

Case G(company ZETA): launched its first digitalization project, focused on the quality control of finished products, with the aim of reducing non-conformities and customer complaints. The project targets the introduction of digital tools based on computer vision algorithms, supporting a more structured and preventive approach to defect management.

2.2 Data Collection and Interview Protocol

To conduct the interviews, a set of four standardized macro-questions was defined and consistently presented to all interviewees. These macro-questions were specifically designed to systematically investigate the main sections of the theoretical framework developed in this research. Each section of the framework was identified and structured based on criteria of conceptual and semantic similarity, in order to ensure coherence between the theoretical constructs and the empirical evidence collected.

The questions were formulated following a semi-structured approach, allowing interviewees to freely express their experiences and articulate their responses in a natural and unconstrained manner. This approach facilitated a more authentic and in-depth narration of project experiences, increasing both the richness and the reliability of the collected information. At the same time, it enabled the emergence of insights, critical issues, and reflections that would have been difficult to capture through closed-ended or highly structured questions.

During the interviews, when relevant topics were not spontaneously addressed by the interviewee, targeted follow-up questions were posed to further explore specific aspects or fill potential informational gaps. This flexibility ensured comprehensive coverage of the research themes while maintaining a high level of comparability across interviews, thereby strengthening the overall robustness of the qualitative analysis.

As anticipated, the four macro-questions were designed to cover specific thematic areas of the framework. These areas are outlined below.

Conceptualization of the Idea and Managerial Support

This section addresses the initial phases of the framework and includes the following design principles: (Figure 2.1)

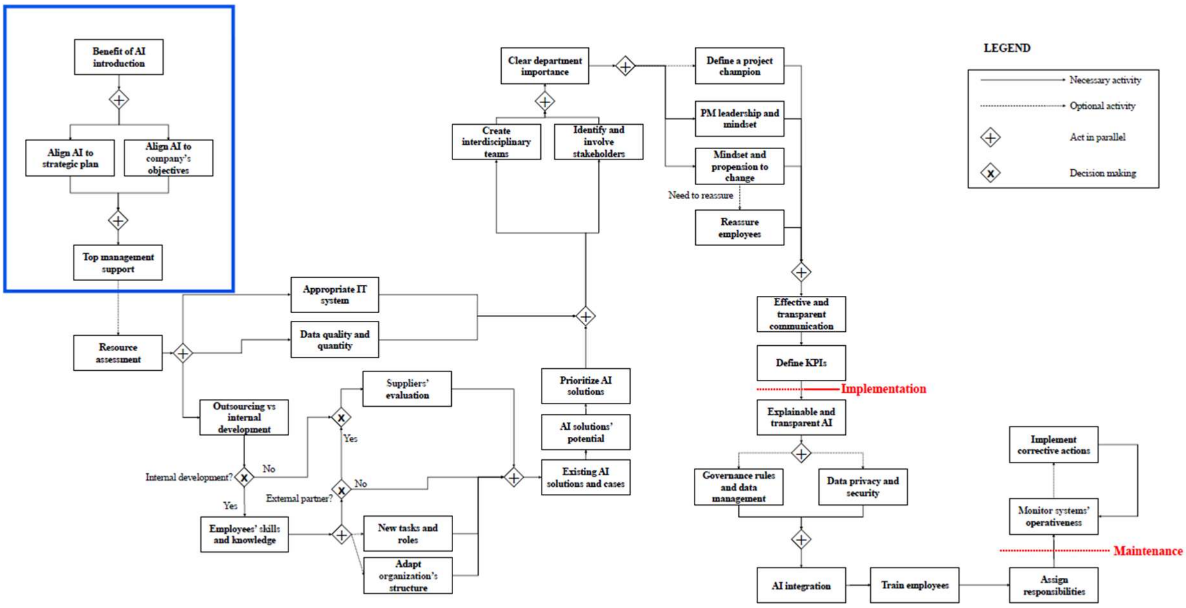


Figure 2.1 First standardized question: Conceptualization of the Idea and Managerial Support

The objective of this section is to assess the organization's level of knowledge and awareness regarding artificial intelligence, with particular reference to the expected benefits of its introduction. Specifically, the analysis focuses on how such benefits were identified and evaluated during the preliminary stages of the project, as well as how AI was proposed and recognized as a potential solution to the problems or opportunities identified.

Furthermore, this section aims to reconstruct the decision-making process that led to the identification of the AI project, analysing the degree of alignment between the initiative and the organization's long-term strategic direction, as well as its coherence with operational and strategic objectives. An additional element of analysis concerns the role played by top management, both in terms of initial support for the project proposal and as an enabling factor for the launch and legitimization of the initiative within the organization.

Requirements Analysis and Solution Identification

This section covers topics related to the analysis and definition of project requirements and includes the following principles: (Figure 2.2)

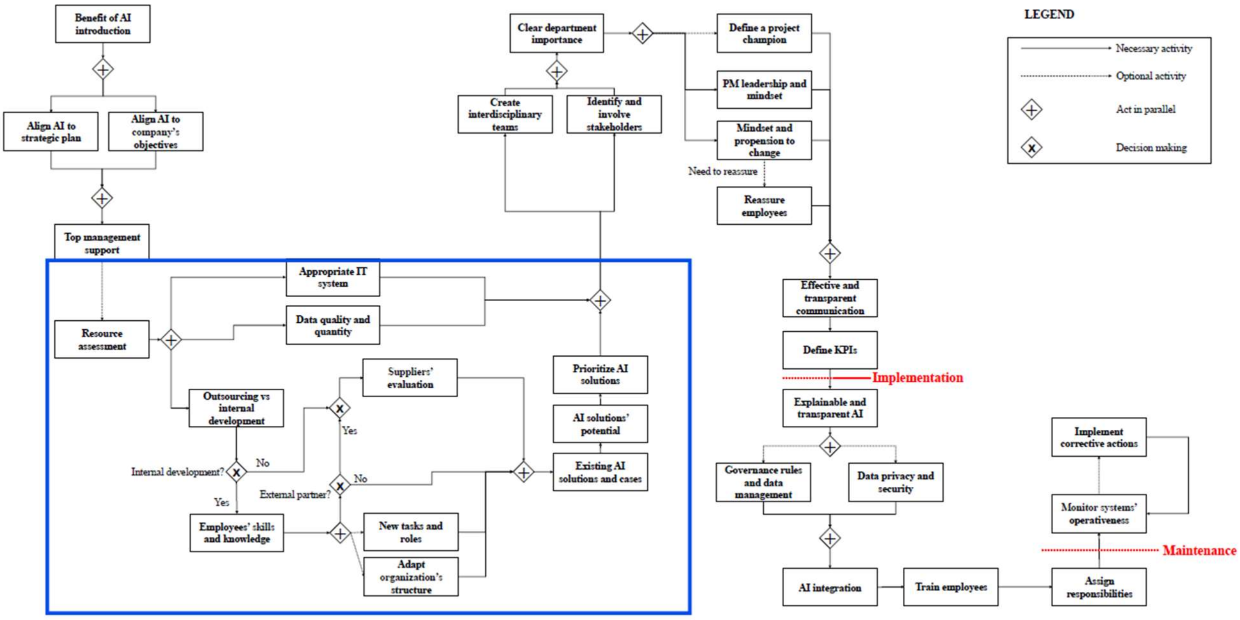


Figure 2.2 Second standardized question: Requirements Analysis and Solution Identification

The objective of this section is to conduct an in-depth analysis of the requirement-definition phases that preceded the operational launch of the artificial intelligence projects. Particular attention is devoted to understanding how organizations assessed the resources needed for the development and implementation of AI solutions, distinguishing between those already available internally and those that needed to be acquired externally.

The analysis considers several key dimensions, including financial and economic aspects, technological and IT infrastructure, as well as human resources and the competencies required for the project. Additionally, the organization's initial level of preparation across these dimensions is examined, together with the ways in which potential gaps were identified and addressed.

Finally, this section explores strategic make-or-buy decisions, analysing the logic behind internal development versus reliance on external vendors, as well as the criteria adopted for the selection of technological partners. These aspects are particularly relevant as they directly affect project complexity, implementation timelines, and the long-term sustainability of the adopted AI solutions.

Team, Leadership, and Stakeholder Management

This section examines issues related to the definition of the project team, the allocation of roles and responsibilities, and the management of both internal personnel and external stakeholders involved in artificial intelligence initiatives.(Figure 2.3)

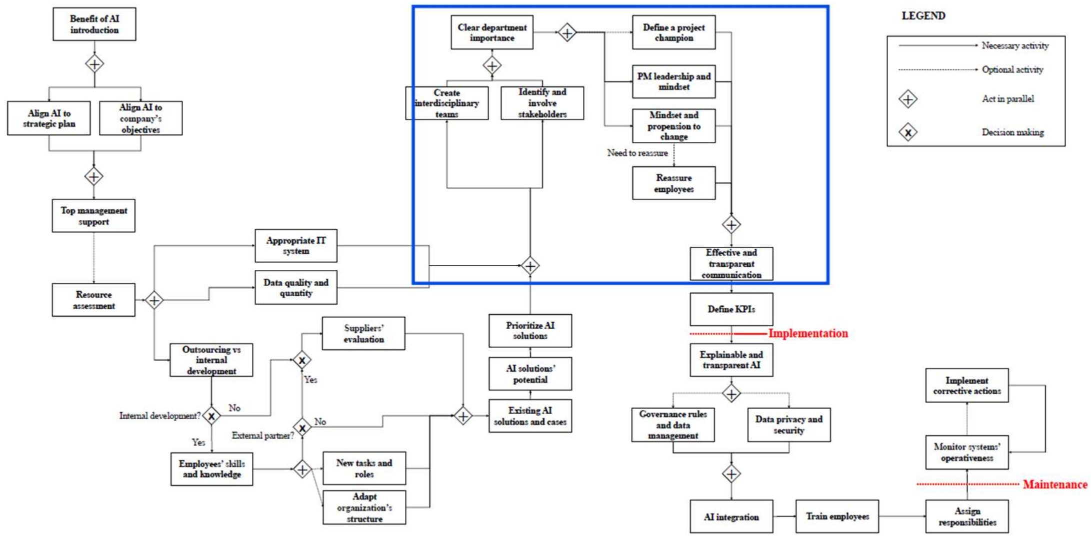


Figure 2.3 Third standardized question: Team, Leadership, and Stakeholder Management

The primary objective is to understand how managers interacted with human resources throughout the different phases of the project, analysing team coordination mechanisms and the strategies adopted to foster collaboration among individuals with diverse skills and professional backgrounds. Particular attention is given to identifying potential resistance or friction from end users of the AI solutions, as well as to the actions taken to address these challenges and their possible impact on project outcomes.

The section also aims to identify the role of leadership within the project, assessing the presence of key figures, such as project champions or internal sponsors, who significantly contributed to the advancement of activities and to overcoming organizational and operational difficulties. Finally, the composition of the project team is analysed in terms of technical, managerial, and transversal competencies, in order to understand how the nature and level of expertise of the involved resources influenced the development and overall outcome of the analysed initiatives.

Deployment and Post-Deployment

This section investigates issues related to the deployment phase of artificial intelligence solutions, data governance and security, and post-implementation activities.(Figure 2.4)

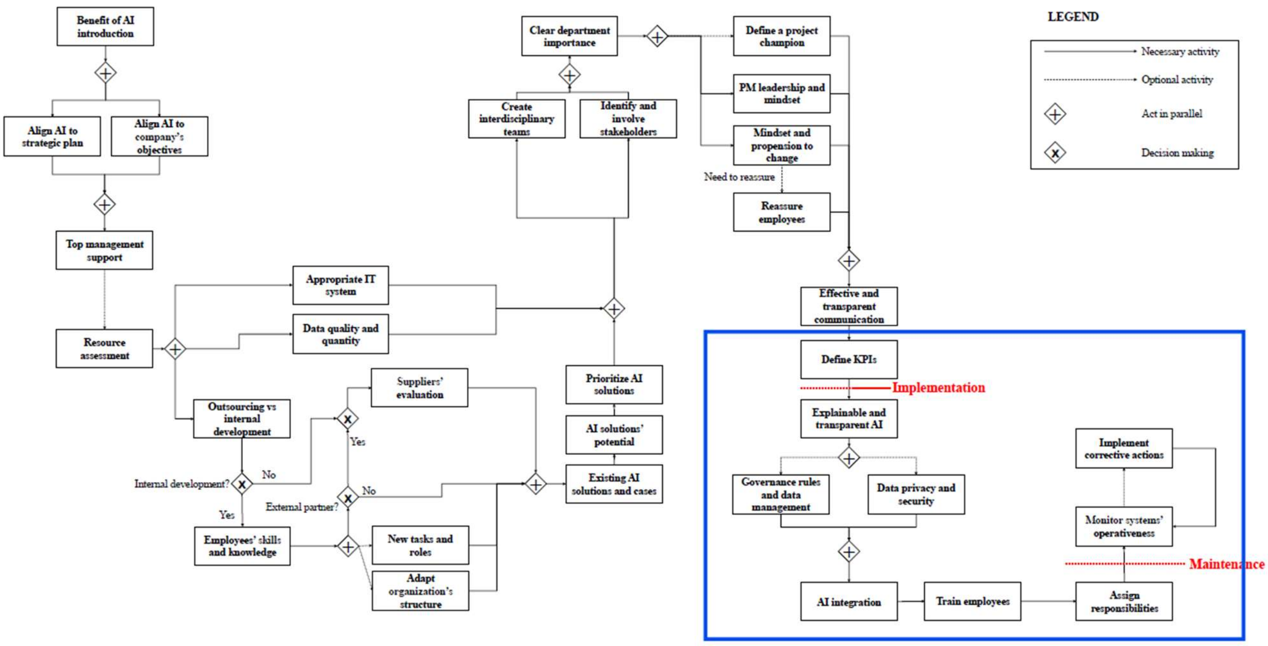


Figure 2.4 Fourth stadardized question: Deployment and Post-Deployment

The objective is to understand how organizations managed post-deployment phases, with particular attention to governance mechanisms adopted to ensure the correct, secure, and compliant use of data, as well as the protection of sensitive information and adherence to existing regulations. The section also explores how training activities were organized for personnel involved in the use and supervision of the system, in order to ensure effective and informed utilization of the implemented solutions.

An additional aspect analysed concerns the presence of performance monitoring systems and continuous evaluation mechanisms for AI solutions, aimed at verifying system stability, alignment with initial objectives, and the potential emergence of critical issues over time. Finally, the strategies adopted for system updates, maintenance, and continuous improvement are examined, in order to assess how organizations seek to ensure the long-term sustainability and value of the implemented artificial intelligence solutions.

3 Qualitative Data Analysis

The data analysis process adopted in this research is structured into two complementary phases: Within-Case Analysis and Cross-Case Analysis, following a qualitative methodological approach aimed at reconciling the detailed examination of individual cases with the ability to identify common patterns across multiple contexts.

In the first phase, the *Within-Case Analysis*, the content of the interviews and the experiences shared by the managers involved in the studied projects are presented and analysed in detail. Each case is examined individually, highlighting how each project fits within the theoretical framework under consideration. This approach allows for the identification of context-specific peculiarities, emphasizing the differences and distinctive characteristics that emerge from the concrete management of AI and machine learning projects in supply chain, Industry 4.0, and production processes. The within-case analysis thus provides an in-depth understanding of individual cases, enabling the documentation of events, decisions, and operational dynamics at a high level of detail.

Subsequently, in the *Cross-Case Analysis* phase, the results of the individual cases are synthesized into a single comparative matrix, which allows for a joint analysis of all the studied cases. The aim of this phase is to identify recurring patterns and significant differences among the various projects, highlighting the impact of different methodologies adopted and the degree of adherence or non-adherence to the theoretical framework. The cross-case approach also allows for drawing more generalizable and transferable conclusions, identifying common elements that may represent emerging best practices, as well as recurring critical issues that may influence the implementation of similar projects in other contexts.

In summary, the combination of these two analytical phases ensures a balance between a deep understanding of individual cases and the capacity to generalize the results, thus providing a comprehensive and detailed view of the adoption and management of AI projects within the studied industrial context.

3.1 Within-Case Analysis

The *Within-Case Analysis* represents the phase in which each project is examined individually, with the aim of highlighting the specific characteristics, challenges, and dynamics that emerged during its implementation. This approach allows for a detailed understanding of the decisions made, the strategies adopted, and the interactions among stakeholders, providing an in-depth view of the context and concrete management practices for each case.

The following section presents the case studies, analysed individually to illustrate the peculiarities and specific experiences of each case study.

Case A

ALPHA is a company operating in the cable manufacturing industry, characterized by a global presence and a customer portfolio spanning numerous industrial sectors. The competitive environment in which the company operates is strongly international and marked by increasing operational complexity, driven both by the diversity of the markets served and by the need to coordinate production and logistics activities on a global scale.

Over recent years, ALPHA has embarked on a structured digital transformation journey that has involved multiple corporate functions across the entire value chain. In particular, the company has promoted and implemented numerous digital innovation projects aligned with the paradigms of Industry 4.0, with a specific focus on the integration of information systems, production processes, and data flows. Digitalization has therefore not been conceived as a set of isolated initiatives, but rather as a strategic lever to improve operational performance and support decision-making processes.

The industry in which ALPHA competes is characterized by relatively low product margins, making operational efficiency a particularly critical factor. In this context, the optimization and improvement of production processes play a central role in the company's strategy. Even incremental improvements, when applied systematically and at scale, can generate significant impacts on costs, final product quality, and operational continuity.

As a result, ALPHA considers production and quality to be key strategic factors for business development and for strengthening its market competitiveness. The adoption of digital solutions and advanced technologies enables the company to monitor and control production processes more accurately, reduce inefficiencies, improve traceability, and support continuous improvement initiatives. From this perspective, digitalization and technological innovation represent fundamental elements for sustaining ALPHA's competitiveness in a sector characterized by strong cost pressure and a high focus on operational excellence.

This context has created favourable conditions for the development of artificial intelligence–based projects within the supply chain. The strong drive toward digitalization and continuous improvement has facilitated the launch and implementation of numerous AI initiatives, primarily aimed at improving production processes and manufacturing lines. Over time, these experiences have contributed to building greater awareness of the potential benefits of AI, as well as a more mature understanding of the operational challenges and critical issues associated with managing such projects.

Within this framework of digital maturity and progressive adoption of advanced solutions, the project analysed in this study is positioned. The initiative stems from the need to leverage the existing information assets and to translate data generated by production processes into actionable insights to support decision-making. Specifically, the project focuses on the use of machine learning software to identify the optimal operating parameters of production line machinery, with the objective of systematically improving the performance of the production system. By analysing large volumes of historical data generated by process instrumentation, the project aims to gain a deep understanding of production line behaviour and to support optimization actions oriented toward efficiency, process stability, and final product quality.

Once the production performance considered strategic for optimization had been identified, the company initiated a preliminary analysis phase aimed at exploring the available solution alternatives. During this phase, a project team was defined with responsibility for clarifying the initiative's objectives, defining economic requirements, and verifying the availability and quality of existing data and infrastructures. In parallel, several technological alternatives were evaluated in order to identify the approach most consistent with operational needs and corporate strategy.

The project team played a coordination role and acted as a connection among the various corporate functions involved. Team members possessed cross-functional skills, both technical and process-related, which were essential for understanding business needs and translating them into clear project requirements. The team included, for example, members from the IT and digital departments, operations managers, product managers, and production managers.

For the identification of the most suitable technological solutions, the company relied on specialized external consultants, selected through a structured tender process. The consultants played an active role in proposing different intervention options, illustrating alternative approaches and their implications in terms of costs, benefits, and implementation complexity. Following this evaluation phase, the adoption of a solution based on artificial intelligence and machine learning techniques emerged as the option with the greatest value creation potential.

Consequently, also thanks to the experience gained in previous AI projects aimed at improving production efficiency, priority was given to the development of an AI-based project among the alternatives considered. This solution was deemed the most appropriate to support the optimization of production performance and to effectively leverage the information assets already available within the company.

Throughout the project, internal stakeholders from the production department were actively involved, particularly operators and specialists with in-depth knowledge of processes and machinery usage. Their contribution proved essential both for guiding the correct development of the AI solution and for assessing the practical applicability and operational feasibility of the initial results generated by the model during the experimentation phase.

More generally, company personnel proved to be highly supportive of innovation and open to change. In this context, the project was received positively, with AI perceived as a tool to support daily activities rather than as a threat. As a result, no significant resistance emerged, substantially facilitating change management activities and promoting rapid acceptance of the proposed solution. As the project was characterized by extended timelines and the need to continue standard operational activities in parallel, a general decline in motivation among both the project team and the involved personnel emerged during the final phase. In this context, the project manager played a central role in reinvigorating the team's commitment and reorganizing activities, refocusing efforts on the completion of the project. This intervention proved essential to keep stakeholders aligned with the final objectives and to ensure sustained engagement through to the closure of the initiative.

Finally, the personnel involved were adequately trained in the use of the tool to ensure correct and consistent application within existing operational processes. At the same time, specific monitoring KPIs were defined to evaluate the success and effectiveness of the solution over time, enabling a structured assessment of the benefits achieved in terms of production performance and decision-making support.

The solution was then coherently integrated into the production line, ensuring alignment with existing systems and procedures, and operational and decision-making responsibilities related to its use were clearly defined. The identified KPIs are continuously monitored to verify the stability of the model's performance and its ability to generate value in the long term.

Given the presence of sensitive data related to strategic production processes, it was also necessary to address and manage specific issues related to data governance and privacy. Appropriate mechanisms for data control, access, and protection were therefore defined to ensure data security and compliance with internal policies and regulatory requirements

Case A framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
Digitalization and production efficiency strategy aligned with project objectives. Consolidated understanding of the benefits of AI in manufacturing contexts.	Economic analysis conducted for budgeting purposes. Outsourcing selected for software development.	Data already available within production systems, adapted to the requirements of the solution. IT infrastructure adequate to support the project.	Line parameter setup processes adjusted. Presence of a dedicated digital projects function. Clear responsibilities for performance monitoring and system control.	Multiple AI projects already implemented within the company. Digital function with consolidated experience in AI initiatives. Project prioritized based on expected value creation.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
High propensity for change and innovation. Strong acceptance of operator-support solutions by personnel. Training provided on tool usage and on new processes for line parameter adjustment.	Absence of a dedicated project champion. Digital team with extensive experience in AI projects. Active role of the project manager in sustaining motivation during final phases. Strong top management support due to the strategic relevance of the project.	Stakeholders identified from the early stages. Project team characterized by a high level of cross-functionality.	Management of strategic data with particular attention to data governance and data privacy aspects.	Definition and monitoring of KPIs. Implementation of structured processes for performance control and system updates.

Figure 3.1 Case A framework adoption

In this case study, a high level of adherence to the reference framework is evident, showing a clear alignment between the theoretical principles and the choices implemented in the project(Figure3.1). In particular, there is a strong connection between the artificial intelligence initiative and the company's overall strategy, which enabled the definition of clear objectives aligned with key business priorities.

The analysis of technical and economic requirements proved to be a crucial element for defining the budget and selecting technological solutions capable of generating the greatest value for the organization, thereby reducing the risk of decisions that might not align with actual operational needs.

Another key factor was the positive mindset of the operators, which facilitated the smooth progress of the project and the adoption of the solution. This was complemented by the presence of an experienced internal team dedicated to the development and management of digitalization projects, providing specialized skills and operational continuity throughout all phases of the initiative. This, together with effective managerial oversight, helped to minimize the emergence of critical issues during the implementation phase, ensuring an overall efficient and seamless execution.

In light of all these aspects, the case study can be considered a clear example of success, having achieved its predefined objectives, ensured effective adoption of the tool, and created tangible value for the organization.

Case B

As previously mentioned, ALPHA is a company that has been pursuing a gradual and structured digitalization journey for several years, leveraging a wide range of technologies, including artificial intelligence solutions, tools related to the Industry 4.0

paradigm, IoT systems, and other advanced digital applications. The objective of this journey is the continuous improvement of internal processes and the overall optimization of the value chain, with a particular focus on supply chain and manufacturing activities, which are considered strategic for the organization's competitiveness.

Alongside its goals of efficiency and production optimization, ALPHA also explicitly pursues a "zero-accident" strategy, aiming to reduce both workplace injuries and near-miss events to zero. Within this strategic framework, the development of a machine vision tool aimed at improving safety within production departments has been introduced, conceived as a lever for both prevention and operational process improvement.

The main objective of the solution is the identification and systematic analysis of near-miss events occurring during operational activities, in order to adopt a more proactive approach to accident prevention. By monitoring interactions between operators, equipment, and the working environment, the tool makes it possible to detect potentially hazardous situations and analyse their dynamics. This contributes not only to reducing risks to workers' health and safety, but also to improving operational efficiency by decreasing slowdowns and interruptions caused by critical events. In this sense, the project is fully aligned with both process optimization objectives and the company's "zero-accident" strategy.

The project originated from a specific initiative of the safety manager who, with the direct support of top management, promoted the adoption of a solution capable of contributing concretely to the achievement of the strategic objectives described above. The presence of strong executive sponsorship facilitated the launch of the initiative and strengthened its legitimacy within the organization.

Once the project proposal had been presented and formally approved, the digital department was involved with the task of establishing a project team characterized by cross-functional skills. This team was responsible for ensuring an integrated view of technical, economic, and operational aspects, as well as for carrying out a structured analysis of project requirements.

To identify the most suitable technology, the company decided to rely on the support of an external consultant, selected through a comparative evaluation process. The consultant proposed several alternative technological solutions, which were assessed by considering the characteristics of the production context, the complexity of the project, and consistency with safety and operational efficiency objectives. To support the decision-making process, comparable case studies were also examined. At the end of this evaluation phase, the previously described artificial intelligence solution was selected, as it was considered the most appropriate in terms of feasibility and potential impact.

Given the innovative nature and specificity of the project, the data required for software development and training were not initially available. A preliminary data collection phase was therefore launched, which lasted several months. During this phase, cameras were installed and used in production areas considered particularly critical, namely those characterized by a higher probability of potentially risky situations for operators. The resulting recordings constituted the informational basis necessary for the development, testing, and subsequent fine-tuning of the machine vision solution.

Since the data used consisted of images depicting operators during working activities, it was necessary to manage project communication with the involved personnel in a clear and transparent manner, in order to facilitate understanding of the nature and objectives of the initiative, as well as the role of operators within the project. Given the workforce's strong propensity for change and innovation, once the motivations behind the project were clarified and approval was obtained from trade union representatives, no significant resistance to the implementation of the solution emerged.

To assess the completion of development and the effectiveness of the tool, specific control KPIs were defined, which continue to be monitored periodically even after the solution's full deployment. At the same time, particular attention was paid to issues of data governance and data privacy, in order to ensure full compliance with current regulations on personal data processing.

Finally, a training program was launched for the safety department personnel, aimed at ensuring the effective use of the tool. The training covered not only operational aspects, but also the ability to interpret, analyse, and leverage the information generated by the system, thereby transforming it into concrete actions for accident prevention and continuous improvement of workplace safety.

Case B framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
Project aligned with efficiency and safety improvement strategies. High awareness of the benefits of AI.	Economic analysis conducted for budgeting purposes. Outsourcing selected for software development.	Data collection through video cameras with significant lead times. IT infrastructure adequate, with the need to integrate video feeds into existing systems.	Definition of new procedures for safety control. Clear responsibilities for system operation and supervision.	Presence of multiple AI projects within the company. Dedicated digital function with consolidated experience. Project prioritization based on expected value.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
High propensity for change. Involvement of operators and trade union representatives required to ensure proper workforce management.	Absence of a dedicated project champion. Digital team with extensive experience in AI. Project manager effective in actively engaging stakeholders. Initiative promoted by the safety department with the support of top management.	Stakeholders identified and involved during critical phases. Cross-functional team and transparent project communication.	Handling of sensitive data, with strong attention to data governance and data security.	Definition and monitoring of KPIs. Structured processes for performance control and system updates.

Figure 3.2 Case B framework adoption

In case B, there is a strong and consistent adherence to the framework, with all pillars being effectively applied in accordance with the specific context of the project(Figure3.2).

The case study demonstrates clear alignment with a long-term strategic vision, encompassing not only digitalization initiatives but also efficiency improvements and safety enhancements. The nature of this project requires significant focus on the management of both operators and stakeholders, while simultaneously demanding careful attention to data governance to ensure compliance, reliability, and the quality of information utilized by the AI system.

At the same time, technical and economic considerations are fully integrated into the decision-making process, ensuring that the solutions selected are both feasible and capable of delivering tangible value to the organization. Effective leadership has played a crucial role in facilitating the smooth progression of the project, maintaining team focus, and addressing potential challenges proactively.

Moreover, the presence of an experienced internal team, specifically dedicated to digitalization initiatives, has further strengthened the project's execution by providing specialized knowledge, operational continuity, and support in navigating complex technical, organizational, and economic decisions. Overall, the combined effect of strategic alignment, strong leadership, and an expert internal team has contributed to a highly effective and well-managed project implementation, highlighting its successful application of the framework in practice.

Case C

BETA is a company operating in the semiconductor sector, specializing in the development of advanced solutions for chip testing and validation. The context in which it operates is highly technological, characterized by a high intensity of innovation, strong R&D activities, and a global supply chain.

Within the company, numerous projects related to digitalization and technological innovation are in place, fostering the development of AI-based initiatives, particularly computer vision tools for processes optimization and quality control, which represent a key element in the reference industry.

At BETA, projects of this type have been developed for several years, and a dedicated team has been established for their implementation. This has enabled the company to build experience and awareness of both the benefits and the organizational and operational implications of these technologies.

The first step of the project is the definition of a project charter, in which the objective, the proposed technological solution, the expected timeline, the budget, and the anticipated economic benefits are clearly defined. Once a positive economic return has been verified, the project is approved.

To gather the information required for project definition, it was essential to establish the project team from the very early stages. This team includes not only the project manager, but also the technical team responsible for software development and the internal stakeholders responsible of the process affected by the initiative.

Following the definition of requirements and project approval by top management, the longest phase of the entire project begins: data collection. Although the presence of a dedicated internal team for this type of initiative allows for deeper knowledge of the production system and some acceleration of the process, several months are still required to obtain a dataset that is adequate for the project's objectives.

Another critical issue concerns the resistance and concerns of operational personnel. To address this aspect, operators are involved in all phases of the project, with the aim of making them feel like active participants in the change rather than external stakeholders. This approach helps to reassure staff, improve the quality of the final outcome, and ensure the most transparent and comprehensive possible understanding of the functioning and potential of the new tool. The processes and roles of operators, who receive appropriate training, are also redefined to include activities related to the control, maintenance, and updating of the implemented solution.

Finally, given that the data used present a low level of sensitivity and criticality, no significant effort in terms of data governance was required.

Case C framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
Digitalization and optimization strategy aligned with project objectives. Established knowledge of AI benefits in production.	Economic analysis conducted for budgeting purposes. Presence of an internal team with expertise in developing AI applications.	Data collection was particularly time-consuming. IT infrastructure adequate, with a need to integrate recordings into existing systems.	Processes adapted for integration of new solutions. Team experienced in AI application development. Responsibilities clearly defined for users and performance monitoring.	Several AI and machine vision projects present in the company. Project prioritized based on expected value and fit with the application context.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
Employee involvement necessary during the project to improve tool performance and reduce resistance. Operators trained on the AI solution after project completion.	Strong top management support for process optimization projects. Good team management capability. Project champion identifiable as the head of the software development team.	Stakeholders identified and engaged throughout the project. Interfunctional team and transparent communication.	Management of non-sensitive data. Data governance and privacy activities were limited. Black-box solution	Definition and monitoring of KPIs. Implementation of structured processes for results control and system updates.

Figure 3.3 Case C framework adoption

Case C highlights a clear and coherent adherence to the theoretical framework and to the pillars that compose it, demonstrating how the reference principles were applied in a systematic and context-aware manner(Figure3.3). The strong strategic alignment of the initiative with the company's objectives facilitated not only the launch of the project, but also its development over time, ensuring continuity and consistency with the organization's overall vision.

The presence of several business cases embedded within a broader digitalization strategy also enabled the company to progressively consolidate and expand its capabilities in the field of artificial intelligence, fostering greater technological maturity and a more informed assessment of the concrete impact of the implemented solutions on operational processes.

A particularly relevant factor in case C is represented by the project manager's skills and leadership in managing the stakeholders and operators involved. The PM adopted an inclusive approach, actively engaging people throughout the different phases of the project with the aim of increasing transparency, reducing resistance, and facilitating the acceptance of the solution within the organization. This management style contributed significantly to creating a climate of trust and collaboration, ultimately supporting a smoother and more effective project implementation.

Case D

GAMMA is an industrial company operating in the field of technological solutions for energy efficiency and the control of industrial and commercial systems, characterized by a strong global presence. The organization demonstrates a pronounced orientation toward innovation, pursued through the systematic adoption of digitalization, process automation, and sustainability-oriented solutions.

This well-established culture of innovation has progressively fostered, within the company, a growing awareness of the potential benefits deriving from the use of artificial intelligence tools. Such awareness has provided the foundation for the launch, in recent years, of several projects aimed at introducing AI-based solutions to support production and operational processes.

One of the first projects initiated in this domain concerned the implementation of a computer vision tool designed to support operators during the manual assembly of electronic equipment. Specifically, the solution was developed to assist in identifying the correct components to be used, with the aim of reducing the incidence of human error in assembly activities, improving the quality of the final product, and decreasing the number of rework operations.

Following the identification of the problem, the company conducted a series of technical and economic analyses to determine the technology capable of delivering the greatest impact in terms of expected benefits. Given that product quality represents a strategic priority for GAMMA, the project was assigned a high level of priority compared to other ongoing initiatives and received strong organizational support.

As this represented one of the company's first projects in the AI domain, GAMMA initially lacked sufficiently mature internal competencies to fully anticipate potential critical issues and to comprehensively assess the expected benefits of the solution. Consequently, a preliminary phase focused on the acquisition of specific knowledge and skills was required, aimed at gaining a deeper understanding of the potential of artificial intelligence and its possible fields of application.

For the definition of the project requirements, which were necessary for the subsequent approval phase, a cross-functional team was established and the needed stakeholders were identified from the early stages, including all the competencies deemed essential for the successful implementation of the initiative. Once the project was approved, data collection was carried out internally, while software development and the implementation of the hardware infrastructure required for the computer vision tools were outsourced to selected external consultants.

Throughout the project, the personnel involved demonstrated a high degree of flexibility and a general openness to change. This was facilitated by the fact that when the goal of the project and the role of the stakeholders ,was properly communicated to them, the solution was not perceived as highly invasive and that operators viewed the new tool as a form of support for their daily activities. As a result, no significant resistance or conflicts emerged among the end users of the solution.

One of the main factors that contributed to delays in the completion of the project was related to the quality of the collected data. In computer vision applications, environmental and lighting conditions have a significant impact on the images captured by cameras. Despite the implementation of corrective actions aimed at improving the performance of the classification models, during the preparation phase for deployment and subsequent scaling across other facilities it became evident that certain environmental factors had been underestimated. This required an additional period of software fine-tuning, leading to an extension of the originally planned project timeline.

Once the solution had been fully implemented, a training program was launched to familiarize personnel with the functioning of the tool, define its modes of use, and clarify roles and responsibilities. At the same time, several business processes were adapted and redesigned to ensure the effective integration of the solution into ongoing operational activities.

Finally, dedicated monitoring dashboards were developed to enable periodic control of the key performance indicators (KPIs) defined prior to deployment. Given that the data used exhibited a low level of sensitivity and criticality, no significant additional effort was required in terms of data governance, allowing the company to focus primarily on operational aspects and the continuous improvement of the implemented solution.

Case D framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
Alignment of the project with the company's strategy and quality standards. Preliminary analysis of AI benefits facilitated by the ongoing digitalization journey.	Financial analysis conducted for budgeting purposes and project approval. Tool development outsourced to external providers.	Extended data collection phase. Insufficient initial quality at go-live, requiring corrective iterations. Overall IT infrastructure adequate to support the project.	Processes adapted to integrate the new tool. The solution supports operators without significantly altering their tasks. Responsibilities clearly defined for system users and performance monitoring.	First machine vision project. High potential impact identified and priority assigned to an AI-based machine vision solution.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
High propensity for change and low invasiveness of the solution. No significant resistance from personnel. Operators trained in the use of the tool.	High strategic relevance and strong top management support. Absence of a project champion with specific experience. Presence of senior managers capable of coordinating stakeholders and maintaining team alignment.	Project scope and roles communicated transparently. Key stakeholders identified and a cross-functional team established.	Management of data considered non-sensitive. Limited data governance and data privacy activities. Black-box solution	Definition of monitoring KPIs and implementation of control and maintenance procedures for the tool.

Figure 3.4 Case D framework adoption

The case under analysis shows a good level of alignment with the reference framework, with overall coherence between the corporate strategy, the defined objectives, and the adopted project choices(Figure3.4). The project is embedded within a clear strategic context, in which the artificial intelligence initiative was conceived as a tool to support business priorities and existing processes.

Personnel management was facilitated by the presence of a mindset generally oriented toward innovation and change, which helped reduce internal resistance and foster acceptance of the proposed solution. At the same time, economic and technical analyses were conducted to assess the feasibility of the project and its compliance with the initial requirements, supporting the decision-making process and the selection of the most appropriate solutions.

However, a relevant critical factor was the limited attention initially devoted to issues related to data quality. The incomplete adoption of data governance and data quality principles led to unforeseen issues during the development phase, resulting in delays and an extension of the project timeline beyond initial expectations.

Despite these challenges, corrective actions implemented once the root cause of the problem was identified allowed the project to return to a proper development path. The solution was ultimately completed and made operational, enabling the achievement of part of the intended objectives. In light of these considerations, the case study can be regarded as an example of partial success, in which strong strategic and organizational alignment was partially compromised by technical challenges but ultimately recovered through effective corrective action.

Case E

DELTA is a multinational group operating in the healthcare sector, characterized by a strongly customer-centric business model and a focus on the delivery of high value-added services. The organization combines specialized clinical expertise, a globally structured distribution network, and complex operational processes, while simultaneously demonstrating a growing attention to digitalization and data-driven decision-making. Within this context, DELTA has undertaken in recent years a structured digital transformation journey aimed at leveraging its corporate information assets and introducing artificial intelligence solutions to support key decision-making processes. This approach has progressively been extended to supply chain and procurement functions through the integration of digital platforms and process automation tools.

As part of this digital transformation path, DELTA implemented a simulation tool based on probabilistic forecasting algorithms and machine learning techniques, designed to support inventory control and management activities. The solution exploits historical company data to simulate different demand and supply scenarios, with the objective of identifying the minimum stock level capable of ensuring the desired customer service level. The main objectives of the initiative were the reduction of inventory holding costs, in order to preserve and strengthen the company's competitiveness, and the release of operators from repetitive, low value-added operational tasks, enabling them to focus on analytical activities, innovation, and continuous process improvement.

Given that the tool had a direct impact on two strategic dimensions for the company, operational costs and customer service level, the project was characterized from its early stages by a high level of priority. The initiative also benefited from strong top management support and was formally sponsored by the Chief Supply Chain Officer, who recognized its potential contribution to the achievement of medium- to long-term strategic objectives.

In order to obtain project approval, DELTA conducted an in-depth analysis of the technical and economic requirements necessary for its implementation. To this end, a project team was established, composed of representatives from the supply chain function and the IT manager, who was considered a key figure both for the technical development of the solution and for ensuring its operational continuity over time. In parallel, external partners were selected for the development of the application software and, once the functional requirements had been defined and the most suitable technologies identified, a cost–benefit analysis was carried out to confirm the economic sustainability and overall validity of the initiative. At this stage, DELTA was able to rely on an already consolidated IT infrastructure and on a data base considered to be of adequate quality for the implementation of the tool.

The project was launched under particularly tight timelines and with strong pressure on delivery schedules, driven by the urgency to achieve tangible results in a short time frame. In this context, insufficient attention could be devoted to issues related to organizational change management and personnel involvement. The definition of roles and responsibilities within the project proved to be partial and fragmented, and it was not possible to invest adequate time in engaging end users or in clearly communicating the benefits and advantages associated with the adoption of the new tool.

Following the implementation phase, the company defined data governance and data security policies, developed performance monitoring systems for the solution, and initiated training activities for the users involved. For approximately one year, feedback was collected from users and several attempts were made to adapt the tool to day-to-day operational needs. Despite these efforts, at present the system, although technically functional and stable, exhibits a limited level of adoption, with many employees continuing to prefer the traditional systems previously in use.

Case E framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
Part of a corporate digitalization journey focused on improving customer service and reducing costs. The digitalization process increased awareness of the benefits of AI.	Financial and technical analyses were conducted. Software development was outsourced to carefully selected external providers.	Adequate IT system. Data were already available and of good quality, requiring only limited adaptation to the software's needs.	New operating modes and procedures were defined for system users. Personnel were trained on the use of the AI application at the end of the project.	The digitalization path facilitated exposure to AI use cases. Project selection was based on the expected economic and organizational impact, prioritizing the most promising solution.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
Despite training and feedback collection, adoption of the solution remained limited. Tight timelines did not allow the issue to be adequately addressed during the project.	Project sponsored by top management. A project champion can be identified in the IT manager with greater experience in digital projects. Leadership was not fully effective in managing staff resistance and engaging end users, resulting in limited use of the tool.	Involvement of external stakeholders. Limited internal communication and lack of clarity regarding the roles of different departments.	Handling of confidential and sensitive data, with strong attention to data governance and data privacy aspects.	Definition of monitoring KPIs and implementation of procedures for system control and updates.

Figure 3.5 Case E framework adoption

The case analysed highlights only a partial adoption of the reference framework. Although many of the pillars were formally fulfilled and correctly applied throughout the project, a significant critical factor emerges with regard to personnel management and the involvement of operators(Figure3.5).

The project shows good strategic alignment with corporate objectives and benefited from strong top management support, elements that enabled a rapid start and completion within the planned timeframe. However, the decision to develop and implement the initiative within a particularly short time horizon limited the ability to adequately manage internal resistance. Operators expressed uncertainty and skepticism toward the new tool, which were not addressed with sufficient graduality and effective communication.

As a result, despite the project being completed on schedule and most of the framework pillars being applied, the level of adoption of the solution remains extremely low. Employees tend to prefer well-established traditional approaches, perceived as more familiar and reliable than the new technology.

Case F

EPSILON is a company operating in the automotive sector, characterized by a complex organizational structure and an extensive global presence. The company covers the entire value chain, from design to industrial production, through to distribution and related services, operating across heterogeneous geographical and regulatory contexts.

EPSILON's operating model is based on high production volumes, an articulated network of plants and international suppliers, and highly interdependent planning and coordination processes. In this context, effective supply chain management represents a critical success factor, both in terms of operational efficiency and continuity of service to final markets.

In recent years, the company has undertaken a structured digital transformation journey aimed at improving the governance of industrial and decision-making processes through the adoption of digital solutions, integrated information systems, and an increasingly data-driven decision-making approach.

As an asset-intensive company competing primarily on cost and quality, a particularly relevant area is the management of machinery maintenance. The strategic objective is to reduce equipment downtime and low value-added activities, which negatively affect the overall efficiency of the production system. Within this context, EPSILON implemented a predictive maintenance algorithm based on machine learning techniques, with the aim of overcoming a traditionally reactive approach to maintenance. Previously, maintenance interventions were triggered only when products began to systematically fall outside predefined technical tolerances, generating inefficiencies and production scrap. The objective of the project was therefore to anticipate such events, proactively plan maintenance activities, reduce the time devoted to manual inspections, and decrease scrap rates.

At the time the project was initiated, the company was pursuing an investment containment strategy aimed at increasing liquidity. As a result, one of the main initial obstacles was project approval, which was rejected three times before being granted, despite the company having implemented similar initiatives in the past and therefore being aware of the potential benefits associated with this type of solution.

To obtain final approval, it was necessary to conduct an in-depth analysis of technical and functional requirements, identify the most suitable tools for implementation, and clearly, systematically, and quantitatively demonstrate the economic and operational benefits of the new technology. To this end, in addition to the project manager, an external vendor was involved in the development of the tool, along with the IT manager, who played a central role in the project by defining requirements, interfacing with external partners, and designing an appropriate data architecture.

An additional enabling factor was the prior implementation of a comparable solution at another plant within the group. This experience made it possible to simplify the requirements analysis process and accelerate the understanding of the project's potential, thereby reducing part of the initial uncertainty.

During the development of the project, however, significant critical issues emerged related to personnel resistance. These resistances stemmed both from widespread distrust of the tool and from fears of potential job losses, as the introduction of the algorithm entailed a substantial reduction in certain traditional operational activities. For this reason, already at the stage of proposing the project to top management, it was necessary to identify new, higher value-added tasks to be assigned to the affected personnel. Nevertheless, these concerns could not be fully addressed until after the system had been put into operation.

In the first months of use, project managers had to actively monitor the adoption of the tool to ensure that employees used the new system rather than continuing to rely on traditional methods. Over time, once employees had understood the stability of their roles and verified the actual effectiveness of the solution, they gradually began to rely on the new system.

In the post-deployment phase, in addition to personnel training activities and the adaptation of business processes, a structured procedure for monitoring system performance was conducted during the first months of operation, in order to verify its reliability and consistency with the initial objectives. Data governance and privacy issues were managed by the IT manager with the support of the external vendor, ensuring compliance with applicable regulations and the security of the information processed.

Case F framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
Progetto avviato in un contesto di riduzione degli investimenti. Condotta una fase preliminare di analisi delle potenzialità dell'AI.	Analisi tecnica ed economica svolta per l'approvazione del progetto. Ricorso a fornitori esterni specializzati.	Sistema IT solo parzialmente idoneo. Necessario il supporto di fornitori per gestione dati e sistema. Dati provenienti dai macchinari esistenti, con necessità di adattamento strutturale.	Eliminazione di attività a basso valore aggiunto e riorganizzazione dei processi. Formazione del personale sulle nuove attività e sull'interazione con la soluzione AI.	Analisi dei benefici economici e organizzativi della soluzione AI. Progetto facilitato dalla presenza di un caso comparabile già implementato in azienda.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
Forte timore del personale legato alla sicurezza del posto di lavoro e al cambiamento delle mansioni. Tentativi iniziali di gestione delle resistenze non efficaci; per vincoli temporali il progetto è proseguito senza affrontare pienamente il tema.	IT manager identificabile come project champion, con esperienza in progetti analoghi. Leadership poco efficace nella gestione dei timori del personale, con conseguenti ritardi nell'adozione, raggiunta solo dopo mesi di supervisione. Supporto limitato del top management, dovuto alla strategia aziendale, con rallentamenti nella fase di avvio.	Stakeholder identificati e informati sin dalle fasi iniziali. Team di progetto interfunzionale definito dopo l'approvazione. Gestione inadeguata delle resistenze degli operatori.	Data governance e data privacy gestite dall'IT manager con il supporto di un vendor esterno specializzato.	Definizione di KPI di controllo. Periodo iniziale di monitoraggio e correzione delle performance del sistema.

Figure 3.6 Case F framework adoption

The case under analysis shows an overall good level of adherence to the reference framework, although it is accompanied by several relevant critical issues that influenced both the project's development and its outcomes(Figure3.6). In particular, the initiative appears to be partially misaligned with the company's strategy during the period considered: the organization was in a phase focused on liquidity accumulation and investment caution, which made it more difficult to obtain full support and rapid approval from top management, who were less inclined to finance new innovative initiatives.

This context had a direct impact on the project's development approach, imposing particularly tight timelines and limiting the ability to devote adequate attention to change management and to the concerns expressed by operators. The reduced level of engagement and communication in the early stages contributed to uncertainty and internal resistance toward the new solution.

As a result, once the tool was implemented in the production environment, the initial level of adoption proved to be below expectations. To address this situation, it became necessary to introduce a period of supervision and on-the-job support for operators, aimed at ensuring compliance with the new processes and gradually supporting the use of the solution. By the end of this support phase, adoption levels progressively improved, making it possible to achieve satisfactory results.

In light of these elements, the project can be considered a case of partial success: although it did not fully realize its potential from the outset due to strategic and organizational constraints, it was ultimately able to achieve its main objectives over time thanks to corrective actions and a strengthening of change support activities.

Case G

ZETA is a small manufacturing company operating in the fasteners industry, specializing in the production of screws for industrial customers. The organization operates primarily in a business-to-business context, characterized by high product quality requirements, stringent technical specifications, and a high level of supply reliability, all of which are essential for maintaining long-term relationships with industrial clients.

The operational model adopted by the company is traditional in nature and is based on well-established production processes developed over time, as well as on a predominantly manual management of control and planning activities. Operational decisions have historically been supported by the direct experience of operators and by the use of poorly structured tools, with limited reliance on integrated digital systems. In particular, final product quality control is carried out through standardized procedures, but it is characterized by a low level of automation and a limited systematic analysis of the collected data, which reduces the ability to promptly identify recurring trends and critical issues.

Within this context, the company launched its first digitalization project, focused on the area of final product quality control, with the objective of reducing the number of non-conformities and customer complaints. The project is aimed at introducing digital tools based on computer vision algorithms, in order to support a more structured, objective, and preventive approach to defect management, overcoming the limitations of traditional manual inspections.

In the absence of prior expertise in digital technologies and artificial intelligence, it was necessary to devote a significant initial phase to the analysis of the available solutions for automating quality control activities. The project was managed directly by the company's owners, as there was no internal specialized staff nor a structured IT function to support the initiative.

As it was not feasible to develop the solution internally, the company opted for a buy strategy, relying on an external provider. After conducting appropriate budget evaluations and analysing the potential of the various solutions available on the market, also by attending conferences and technology-related events, an enterprise-level solution was selected. This choice was driven by the intention to contain project-related risks and, ideally, to reduce the overall project completion time. The provider supplied both the hardware and software infrastructure, thereby avoiding potential issues related to the integration of the two components.

During the implementation phase, two main critical issues emerged: the adaptation of the software to company-specific data and the management of the involved personnel. Since the solution was based on a pre-trained software, it was not necessary to invest significant resources in algorithm customization; however, a fine-tuning phase and the precise definition of quality criteria, namely acceptable tolerances, for each SKU proved to be essential. In the absence of personnel dedicated to projects of this kind, part of the internal resources had to be reallocated to carry out these activities in parallel with ordinary operations, with the support of the provider to transfer the competencies required for the correct use of the tool. As a result, this phase took several months and exceeded the initial expectations of the project promoters, also due to the limited attention initially paid to the impact of environmental factors (such as lighting conditions, component positioning, and variability of the production context) on the performance of computer vision algorithms, which in some cases made it necessary to repeat the configuration procedures.

A further critical aspect concerned the management of organizational change. Operational staff proved reluctant to collaborate and to adopt the new tool in their daily activities. Although the potential benefits of the solution were generally understood, managers, lacking in-depth technical expertise, were not able to clearly and effectively communicate the reasons why the computer vision algorithm was more efficient and reliable than the traditional methods previously in use.

For these reasons, despite the fact that the tool is technically functional and that personnel have been adequately trained in its use, the level of adoption of the solution remains extremely limited, thereby reducing the overall impact of the initiative on the company's performance.

Case G framework adoption

Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
First digitalization project, considered strategic for the company. A thorough preliminary analysis of the benefits and potential of AI was conducted.	A financial analysis was carried out to assess economic feasibility and investment constraints. An enterprise solution provided by specialized external vendors was selected.	Hardware and software were entirely supplied by third parties. Data collection was highly time-consuming, and the underestimation of technical aspects led to significant delays.	Partial impact on operational activities. Personnel were trained on the use of the tool and on how to interact with it.	An analysis of the solution's benefits was performed. Alternative technologies were evaluated, and the option offering the best cost–benefit trade-off was selected.
Employees' management	**Top Management**	**Stakeholders management**	**Governance & communication**	**Post deployment**
Strong resistance from operators. Despite explanatory efforts, traditional tools continued to be preferred.	Absence of a project champion. Leadership was not effective in managing resistance. The initiative was promoted by top management.	A limited number of stakeholders were involved. External vendors were managed effectively, while internal stakeholders (operators) were only partially managed.	Low sensitivity of the data processed. Limited relevance of data governance and data privacy issues.	An initial phase of monitoring and performance adjustment of the tool was initiated.

Figure 3.7 Case G framework adoption

The analysed case highlights a partial adoption of the reference framework. Although several pillars and principles were considered and applied throughout the project, a number of significant critical issues emerged, attributable to the missing or incomplete implementation of specific key elements of the framework(Figure3.7).

In particular, despite a clear awareness of the strategic importance of data quality, this aspect was initially underestimated during the operational phases of the project. This shortcoming led to issues during the development and integration of the solution, making subsequent corrective actions necessary. These interventions resulted in extended timelines compared to the initial forecasts and had a negative impact on the overall efficiency of the project.

At the same time, another critical area concerns change management and the handling of staff resistance. The organization was unable to implement sufficiently effective measures to support operators throughout the adoption process of the new tool. As a result, employees showed a strong reluctance to modify established working practices, continuing to rely on traditional approaches perceived as more familiar and reliable.

These issues, affecting both technical and organizational-cultural dimensions, limited the overall effectiveness of the initiative. The case therefore illustrates how an incomplete implementation of the framework can undermine project outcomes, even when there is a partial adherence to its fundamental principles.

Identify Successful case studies

Based on the cases analysed previously, it is possible to distinguish among the different cases according to the degree of success of the initiatives presented. In particular, this thesis adopts a classification framework that allows for a consistent evaluation of the outcomes of the analysed projects.

A successful case is defined as one in which the implemented tool is fully functional and achieves a good level of user adoption immediately after the implementation and integration phases within the company's systems, while also complying with the planned timelines and budget.

A non-successful case, on the other hand, refers to situations in which, at the time of the interview, the implemented solutions are either not functional or exhibit an insufficient level of adoption, such that the predefined objectives are not achieved.

Finally, a partially successful case is defined as one in which, at the time of the interview, the proposed solutions are functional and show a good level of adoption, but achieving these results required additional time and costs that were not initially anticipated.

Based on these definitions, it is therefore possible to proceed with the classification of the analysed cases as follows(Table3.1)

Table 3.1 Cases classicfication

PROJECT	CLASSIFICATION
A	**Success**
B	**Success**
C	**Success**
D	**Partial**
E	**Unsuccess**
F	**Partial**
G	**Unsuccess**

3.2 Cross-Case Analysis

3.2.1 Cross-Matrix

Once the within-case analysis was completed, the subsequent step in the case study analysis process was the cross-case analysis. The purpose of this phase was to systematically compare the different cases examined, in order to identify recurring patterns, significant differences, and common relationships among the emerging findings.

Specifically, a comparative matrix was developed based on the matrix containing the main insights derived from the within-case analysis of each individual case. The information included in this table was appropriately coded and categorized, using the principles that constitute the reference framework as the level of analytical granularity. This approach ensured methodological consistency between the analysis of individual cases and the subsequent comparative phase.

After completing the comparative matrix, similarities and differences across the cases were examined in depth, while also assessing their degree of alignment with the adopted theoretical framework. This comparison made it possible to highlight convergences and divergences in behaviours, project choices, and observed outcomes across the different contexts analysed.

Whenever deviations from the theoretical framework emerged, these were subjected to a dedicated analysis aimed at understanding their implications and consequences within the specific case studies to which they referred. This made it possible to gain a deeper interpretation of each case's specificities and to contextualize any departures from the reference theoretical model.

The complete table is reported in the Annex, while any specific analyses of the results are presented in the following section, limited to the relevant columns and the associated case studies.

3.2.2 Comparative Analysis

Once the results emerging from the cross-matrix were thoroughly analysed, it is possible to clearly observe that, across the case studies considered, there was a strong and widespread adherence to the theoretical framework and to the principles that constitute it. This evidence suggests that the analysed cases are largely aligned with the proposed conceptual structure, thus providing solid empirical support for the theoretical foundations on which the framework was developed.

In particular, the comparative analysis highlights that 20 principles were addressed systematically and consistently across all the examined case studies. By way of example, these include: *Benefits of AI adoption*, *Resource assessment*, *Outsourcing vs. internal development*, *Appropriate IT system*, *Adapt organization's structure*, *AI solutions' potential*, and *Train employees*. The recurring presence of these principles in all the analysed cases indicates that they are perceived by the interviewees as fundamental and indispensable steps in the design and implementation process of artificial intelligence solutions.

This result shows that, regardless of the specific context or organizational characteristics of each case, these principles are recognized as key elements for project success, significantly guiding both decision-making processes and the actions undertaken. Consequently, the high level of convergence observed further reinforces

the validity and relevance of the framework's core principles, confirming their practical applicability and their consistency with the empirical evidence emerging from the case study analysis.

Alignment of AI with business objectives and strategic plan

The principles *Alignment of AI with business objectives* and *Alignment of AI with the strategic plan* were followed in 6 out of 7 cases, clearly highlighting how the alignment between artificial intelligence initiatives and business objectives, as well as with the organization's overall strategy, is considered a factor of primary importance during the initial project launch phase(Table3.2).

This evidence suggests that, in most of the analysed cases, organizations considered it essential to ensure coherence between the adoption of AI solutions and corporate strategic priorities, in order to maximize the value generated and reduce the risk of initiatives that are disconnected from actual business needs. Focusing on these principles from the very early stages of the project enables organizations to properly guide technological, organizational, and economic decisions, ensuring that investments in AI are justified not only from a technical perspective, but also from a strategic one.

The strong adherence to these principles also indicates a growing organizational maturity in viewing AI not merely as a technological tool, but rather as a strategic lever to be integrated within a long-term vision.

Table 3.2 Comparative analysis: Alignment of AI with business objectives and strategic plan

PROJECT	Organization's Strategy		
	Benefits of AI adoption	Alignment of AI with business objectives	Alignment of AI with the strategic plan
A	Yes	Yes	Yes
B	Yes	Yes	Yes
C	Yes	Yes	Yes
D	Yes	Yes	Yes
E	Yes	Yes	Yes
F	Yes	No	No
G	Yes	Yes	Yes

The only exception to this trend emerges in Case F. In this project, the company was undergoing a phase of investment reduction, driven by specific strategic needs and a focus on future objectives considered to be of higher priority. Within this context, the launch of an artificial intelligence project, typically characterized by high capital intensity and delayed economic returns, was not viewed positively within the organization.

This lack of alignment between the AI project and the corporate strategy triggered a series of cascading effects that negatively impacted other principles of the theoretical framework as well. In particular, the first aspect to be affected was top management support, which showed significant difficulty in approving and sustaining the initiative. The absence of a clear link between the project and the strategic priorities of that period weakened the perceived value of the investment, making it more challenging to justify the allocation of financial and organizational resources.

The misalignment observed in Project F highlights the potential critical issues that may arise when AI initiatives are launched without a clear connection to business objectives and the strategic plan. This evidence further reinforces the importance of these principles as guiding elements during the initial phases of AI project design and implementation.

Data quality & quantity

In all the cases analysed, the interviewees explicitly acknowledged the critical importance of the quality and quantity of the data collected for the proper functioning of artificial intelligence solutions. In particular, a widespread awareness emerged that the availability of adequate, accurate, and representative data constitutes a fundamental prerequisite for ensuring the reliability of the results produced by the system and for achieving the project objectives.

However, despite this shared awareness, in two of the projects considered there was a concrete underestimation of the specific technical requirements related to data(Table3.3).

Table 3.3 Comparative analysis: Data quality & quantity

PROJECT	Data & Infrastructure		
	Appropriate IT system	AI integration	Data quality and quantity
A	Yes	Yes	Yes
B	Yes	Yes	Yes
C	Yes	Yes	Yes
D	Yes	Yes	No
E	Yes	Yes	Yes
F	Yes	Yes	Yes
G	Yes	Yes	No

In these cases, although project managers were theoretically aware that the use of inadequate data could significantly compromise the overall performance of the artificial intelligence solution, the operational and technical aspects related to data management were not addressed with a sufficient level of depth during the initial phases of the project. In particular, key elements such as data structure, actual data quality, completeness, and the pre-processing requirements imposed by the algorithm were assessed only partially or superficially, with the resolution of these issues being postponed to later stages.

The main problems emerged clearly in projects D and G. Both cases involved machine vision initiatives and, in both situations, the project managers were aware that specific environmental conditions, especially variables related to lighting, could have a substantial impact on the algorithm's ability to correctly recognize and classify the images provided as input to the system. Despite this initial awareness, the complexity of the issue was underestimated, resulting in an inadequate management of data acquisition conditions from the early project stages.

As a consequence, once these issues became evident, corrective actions on the collected data were required, involving data adaptation and restructuring to ensure compatibility with the specific requirements of the artificial intelligence solution. These corrective activities inevitably led to a significant extension of the project timeline, with delays that exceeded the expectations defined during the planning phase.

This gap between the conceptual awareness of the importance of data and its actual operational management generated several execution-level challenges, highlighting how data management represents not only a well-recognized topic in the literature but also one of the most complex and recurring challenges in the practical implementation of artificial intelligence projects.

Existing AI solutions and Presence of a project champion

The principles "Existing AI solutions and cases" and "Define a project champion" represent two elements of the framework over which management generally has a more limited level of control compared to other stages of the project process. The availability of analogous initiatives already implemented within the organization, as well as access to sufficiently detailed, structured, and comprehensive case studies, is not a factor that can be directly influenced by the project manager, especially during the early phases of project initiation. These elements largely depend on the organization's history, its level of digital maturity, and the experience accumulated over time through comparable projects.

Similarly, the identification of a project champion is strongly conditioned by the presence within the organization of individuals who have developed significant prior experience in managing and delivering artificial intelligence projects or related technological initiatives. The possibility of appointing an effective project champion therefore presupposes the existence of a resource with consolidated skills, and practical knowledge of the application domain, conditions that are not always met. Consequently, while the project manager may facilitate the recognition and valorisation of such figures when they are present, their actions alone are not always sufficient to ensure the actual identification or availability of a suitable project champion.

The analysis of the case studies shows that not all the organizations examined could rely simultaneously on both a clearly identifiable project champion and the presence of comparable prior AI initiatives. In particular, although some companies exhibited at least one of these two elements, only two cases were found to be lacking with respect to both principles.

Table 3.4 Comparative analysis: Existing AI solutions and Presence of a project champion

PROJECT	AI knowledge	Top Management
	Existing AI solutions and cases	Define a project champion
A	Yes	No
B	Yes	No
C	Yes	Yes
D	No	No
E	Yes	Yes
F	Yes	Yes
G	No	No

As highlighted in the summary table(Table3.4), cases D and G both exhibit a dual shortcoming: on the one hand, the absence of prior cases or analogous solutions to serve as references, and on the other, the lack of a clearly identified project champion. A further relevant aspect is that, in both cases, these initiatives represented the first artificial intelligence and machine vision projects implemented within the company. This combination of factors meant that, at the time of project initiation and development, the organizations could not rely on internal prior experience, consolidated competencies within the project team, or best practices already tested in similar contexts.

In this setting, it is plausible to hypothesize that the simultaneous absence of prior references and of a project champion contributed to an underestimation of certain technical criticalities, particularly those related to data quality, structure, and suitability. As discussed in the previous paragraph, significant data-related issues emerged precisely in cases D and G, suggesting a possible relationship between the lack of prior experience and the difficulty in promptly recognizing the operational impact of these aspects on the overall performance of the AI solution.

By way of comparison, cases A and B display a different configuration. Although these projects could not rely on a single formally identified project champion, they benefited from previous organizational experience in initiatives characterized by similar features, as well as from the presence of an internal function dedicated to digitalization and innovation projects. This organizational setup made it possible to involve several individuals with relevant technical and managerial competencies within the project team, who were able to contribute significantly to managing the complexities typical of an AI project, effectively compensating for the absence of a single, clearly defined project champion.

Overall, the empirical evidence suggests that the combination of a lack of prior experience and the absence of a dedicated reference figure may represent a potential risk factor for the success of an AI project, increasing the level of uncertainty across the different phases of implementation. At the same time, the results indicate that the presence of a project

champion, while potentially playing an important role in facilitating the management of critical issues, cannot be considered a strictly necessary condition for project success. Consistently with the theoretical framework, the project champion instead emerges as an enabling and optional element, whose absence can be compensated for by adequate levels of distributed competence, organizational experience, and dedicated innovation structures.

Mindset and propensity to change & Reassure employees

The principles “Mindset and propensity to change” and “Reassure employees” are closely interconnected and mutually dependent, forming two fundamental pillars within the theoretical framework. According to the relevant literature, the success of a technological innovation project, and in particular of an artificial intelligence project, critically requires a positive attitude toward change among employees. This aspect becomes even more significant when considering the end users of the tool, that is, those who will interact with the AI solution on a daily basis and will ultimately determine its actual level of adoption and usage.

For a project to be successfully implemented, it is therefore essential that personnel perceive innovation as an opportunity to improve processes and enhance their work activities, rather than as a threat to job stability or to their existing responsibilities. From this perspective, technology, and artificial intelligence in particular, should be interpreted as a supportive tool for decision-making and operational activities, capable of assisting the operator and increasing efficiency, rather than replacing them.

If this mindset is not initially present within the organization, the literature emphasizes the importance of acting promptly through targeted actions of communication, engagement, and reassurance of employees. Proactive management of perceptions, concerns, and resistance thus becomes a key factor in reducing dissatisfaction, fostering acceptance of the solution, and creating the organizational conditions necessary for the AI project to fully realize its potential.

Table 3.5 Comparative analysis: Mindset and propensity to change & Reassure employees

PROJECT	**Employees' Management**	
	Mindset and propensity to change	Reassure employees
A	Yes	Not needed
B	Yes	Partial
C	No	Yes
D	Yes	Not needed
E	No	No
F	No	No
G	No	No

In the cases analysed, three projects were identified that failed to align consistently with the principles "Mindset and propensity to change" and "Reassure employees," namely projects E, F, and G(Table3.5). In all three instances, management was unable to address employee dissatisfaction and resistance in a timely and effective manner, resulting in direct consequences on the adoption of the artificial intelligence solution.

In project E, in particular, the management of these aspects was virtually absent. During the execution of the project, communication with the end users of the tool was extremely limited, and no targeted actions were implemented to engage or reassure personnel. As a result, once the project was completed and the AI solution put into production, a widespread attitude of reluctance and mistrust toward the tool emerged, significantly limiting its actual usage.

In projects F and G, by contrast, employee resistance was known from the early stages of the project, and an initial attempt was made to address the issue. However, the urgency imposed by project timelines, combined with the low priority assigned to these organizational dynamics, led management to proceed with implementation without dedicating sufficient resources or attention to engaging with operators. In these cases as well, the absence of a structured and continuous intervention resulted in low adoption of the solution, consistent with theoretical expectations.

Project F, however, represents a partial exception to the other two cases. Unlike E and G, after the AI tool was introduced into production, corrective actions were undertaken to improve employee engagement and reduce resistance. These interventions eventually allowed the project to achieve acceptable levels of usage over time. It is important to note, however, that the time required to reach this outcome was substantial and could likely have been avoided if the issue had been addressed in a more structured and proactive manner during the early stages of the project.

Conversely, the other analysed projects did not show significant challenges regarding the adoption of the AI application. Projects A, B, and D demonstrated a strong propensity for change and innovation, which facilitated staff acceptance of the solution. Finally, project C highlights how initial resistance from operators can be effectively managed and overcome through active engagement of personnel during the project, providing a concrete demonstration of the tool's potential and the operational benefits resulting from the introduction of the new AI solution.

Top management support

As previously noted, in case study F, the lack of adequate alignment between the company's overall strategy and the specific objectives of the project directly resulted in insufficient support from top management. In a context where the organization was pursuing different strategic priorities, the artificial intelligence project was not perceived as fully consistent with the company's short- and medium-term strategic guidelines, and therefore appeared less relevant in the eyes of the executive leadership. This misalignment negatively impacted resource availability, slowed decision-making processes, and more generally hindered the ability to fully and convincingly support the initiative throughout the various phases of development and implementation.

Within the analysed sample, case F represents the only instance in which the absence of this principle was clearly observed. In all other case studies, top management support was present, albeit at varying levels of intensity, confirming that strategic alignment constitutes a fundamental enabling condition for the success of AI projects. Although this element is generally not under the direct control of the project manager, interviewees acknowledged the crucial role of top management commitment in facilitating project progress, overcoming potential organizational obstacles, and legitimizing the initiative within the company. In this regard, leadership support emerges as a key factor not only for initiating the project but also for ensuring its continuity, sustainability, and long-term success.

Table 3.6 Comparative analysis: Top management support

PROJECT	Top Management
	Top management support
A	Yes
B	Yes
C	Yes
D	Yes
E	Yes
F	$\boxed{\text{No}}$
G	Yes

Top management support has proven, in the majority of cases analysed, to be a decisive factor in facilitating both the initiation and the effective continuation of artificial intelligence projects(Table3.6). Approval and sponsorship from senior leadership significantly reduce challenges related to budget approval processes, ensure adequate allocation of resources, and guarantee proper prioritization of the project relative to other ongoing initiatives. Furthermore, top management commitment helps legitimize the project within the organization, promoting the engagement of various business functions and supporting the project team in overcoming operational and organizational obstacles.

In contrast, in case study F, the project repeatedly faced difficulties precisely due to limited support from top management. On several occasions, the initiative was delayed or temporarily blocked, necessitating the execution of numerous in-depth technical and economic analyses to clearly and unequivocally demonstrate the potential value of the project. This misalignment between top management and the project objectives led to the imposition of strict constraints on budget and timelines, which negatively affected the overall management of the project.

Specifically, these constraints limited the ability to dedicate sufficient time and attention to managing organizational and human aspects, such as employee engagement and addressing resistance from operators. As a result, certain issues that could have been addressed more effectively in the early phases emerged more prominently in later stages, generating the problems already highlighted previously. This case further confirms that top management support is not only an enabling factor but also a key condition for ensuring the long-term success and sustainability of AI projects.

PM leadership and mindset

The principle related to the project manager's mindset concerns their ability to guide people throughout the entire project journey, maintaining a high level of focus and engagement toward the final objective. In particular, the PM is required to effectively manage the human and organizational dynamics that may arise during the project, addressing potential slowdowns caused by employee resistance, a decline in the priority perceived by the team, or discouragement resulting from issues encountered during the implementation phase.

An appropriate mindset therefore enables the project manager not only to coordinate operational activities, but also to support the team during challenging moments, fostering a climate of trust, motivation, and results orientation, key elements for ensuring the continuity and overall success of the project.

Table 3.7 Comparative analysis: PM leadership and mindset

PROJECT	Top Management
	PM leadership and mindset
A	Yes
B	Yes
C	Yes
D	Yes
E	No
F	Partial
G	No

The presence of effective leadership proved to be a relevant factor in fostering the successful completion of the projects analysed(Table3.7). In particular, Projects A, B, and C can be considered jointly, as they are characterized by a managerial approach capable of effectively addressing and overcoming organizational and human-related challenges, albeit in different contexts and facing distinct issues.

In Cases A, B, and C, the project manager demonstrated a mindset oriented toward people engagement and the maintenance of a strong focus on the final objective. In Project A, which was characterized by long development timelines and a direct impact on the production line, the prolonged duration of the activities had progressively reduced the level of attention and involvement of both the team and internal and external stakeholders. At this critical stage, the PM intervened by reorganizing the team's activities and priorities, thereby realigning efforts around the project, reigniting interest, and bringing the initiative to completion effectively and within a short timeframe.

In Project B, leadership emerged through the ability to manage particularly sensitive issues, such as concerns related to operators' privacy arising from the introduction of camera-based data collection systems. The manager was able to involve labor unions from the early stages and to establish a transparent dialogue with operators, clearly explaining the objectives and methods of the project. This approach made it possible to transform potential resistance into active support for the initiative.

Similarly, in Case C, management demonstrated the ability to address staff resistance by continuously involving operators throughout the entire project development cycle. This participatory approach fostered alignment with the project's objectives and helped overcome initial skepticism, thereby facilitating the adoption of the artificial intelligence solution.

Case D, although affected by delays due to unforeseen technical issues, particularly those related to data quality, also highlights effective leadership. The project leader succeeded in keeping the team cohesive and focused on the timely resolution of the problem, allowing the critical issues to be addressed without compromising the overall progress of the project.

By contrast, Case F is characterized by only partially effective leadership. During the development phases, the project manager was unable to adequately align operators with the project's objectives, underestimating the weight of internal resistance. This shortcoming had negative repercussions on the adoption of the tool once it was put into production. However, in the post-implementation phase, management undertook corrective actions, recognizing that operators' concerns were mainly related to job security. Through a period of supervision and guided use of the tool, and by clearly demonstrating that the introduction of the solution would not entail negative employment consequences, it was possible over time to achieve a satisfactory level of adoption.

Finally, in Cases E and G, management failed to demonstrate effective leadership. Unlike Cases D and F, no corrective actions were implemented to counter internal resistance and realign the team with the project, significantly undermining both adoption and the overall success of the initiatives.

It is therefore evident that effective leadership can have a significant impact not only on the initiation of a project, but above all on its continuation and successful completion. A project manager endowed with strong leadership capabilities is able to adopt a structured and informed approach to project management, fostering team coordination and maintaining a high level of focus on predefined objectives, even in complex or highly dynamic contexts.

In light of the cases analysed, the project manager's leadership clearly emerges as a fundamental enabling factor for ensuring project continuity, effectiveness, and resilience, playing a decisive role in transforming operational and organizational challenges into opportunities for learning and improvement within the overall project process.

Explainable and transparent AI

This pillar concerns the importance of developing and implementing artificial intelligence solutions that are transparent and whose results are interpretable and understandable by operators and other relevant stakeholders. From a theoretical perspective, the ability to understand the internal functioning of the tool and the logic underlying the decisions generated by AI represents a relevant factor in fostering trust, acceptance, and a conscious and informed use of the technology.

Table 3.8 Comparative analysis: Explainable and transparent AI

PROJECT	Governance & Communication
	Explainable and transparent AI
A	No
B	No
C	No
D	No
E	No
F	No
G	No

However, the analysis shows that the practical applicability of this principle is rather limited in the observed contexts(Table3.8). Many of the AI solutions currently adopted by organizations are in fact designed to operate as true black boxes, that is, systems capable of producing effective and reliable results without fully explicating the internal processes that lead to such outputs. Numerous algorithms underlying the most widespread AI solutions, although highly performant and well suited to project objectives, do not allow for a clear and immediate understanding of the underlying decision-making mechanisms.

This evidence is also reflected in the analysed case studies. In most of the projects, business objectives did not require a detailed understanding of the AI's "reasoning" processes, but were instead focused on achieving specific operational, economic, or performance-related outcomes. Consequently, the interpretability of the tool was not considered a priority requirement, nor an aspect in which to invest additional resources during the design and implementation phases.

In light of these considerations, it can be stated that the principle of Explainable and Transparent AI cannot be regarded as strictly necessary for the completion and success of an artificial intelligence project, at least within the analysed contexts. At the same time, the limited attention devoted to this pillar does not allow its potential value to be excluded. Indeed, no empirical evidence emerges that conclusively refutes the idea that transparency and interpretability may represent an optional yet enabling element, capable of facilitating project implementation, improving user acceptance, and strengthening trust in the technology, especially in contexts characterized by greater decision-making complexity or by more significant ethical and organizational implications.

Success Analysis

This paragraph of the comparative analysis presents a comprehensive comparison of the cases, examining them in their entirety to understand how the overall level of adherence to the theoretical framework influences the outcome of a project. The analysis focuses on identifying the ways in which full and systematic application of the framework contributes to the success of a case, while deviations or partial implementation are associated with partial success or failure. By highlighting these differences, the discussion aims to provide a deeper understanding of the critical role that adherence to the framework plays in determining the effectiveness and overall results of AI project implementation.

Successful cases

The successful cases identified and analysed in this research are A, B, and C. The analysis clearly shows that these are the only three cases that, taking into account the considerations previously discussed regarding the principle of “Explainable and Transparent AI” and the project timeline, demonstrate a full and coherent adherence to the reference theoretical framework.

In contrast, the cases classified as partial successes or failures exhibit at least one of the theoretical principles of the framework that is either not applied, only partially applied, or introduced in an unstructured manner. These deviations are particularly evident with respect to the principles that are most critical to the sustainability and effectiveness of AI projects, highlighting how the lack of compliance with even a single element can significantly affect the overall outcome of the initiative.

This empirical evidence strengthens and lends greater credibility to the central thesis of the research, according to which a correct, systematic, and comprehensive application of the theoretical framework represents a key factor for the successful development of artificial intelligence projects.

Partial Success and Unsuccess

Once it has been established that adherence to the framework represents a key element for the success of an AI project, it becomes necessary to further investigate what differentiates a partially successful case from an unsuccessful one. By jointly analysing the results emerging from the cross-case matrix and the qualitative evidence reported in the within-case analysis, it can be observed that, in both types of cases, the failure to apply certain principles of the framework generated critical issues during the implementation and execution phases of the projects.

In particular, recurring problems related to data quality and personnel management emerged both in unsuccessful cases and in partially successful ones. Poor data quality, observed in cases D and G, required an extension of the implementation timeline in order to achieve information levels adequate for the proper functioning of the AI solutions. At the same time, cases E, F, and G experienced issues related to human resource management and end-user involvement, which resulted in a lower-than-expected level of tool adoption during the go-live phase.

Given that both types of cases exhibit largely similar shortcomings and challenges, it is therefore essential to understand which factor ultimately determined the difference in project outcomes. In this regard, the analysis of the cross-case matrix makes it possible to identify the principle that most clearly differentiates the two contexts and to understand how it influenced the results achieved.

The analysis shows that the only truly distinguishing element is the presence, or absence, of effective leadership on the part of the Project Manager, captured by the principle of *PM leadership and mindset*. In particular, this principle proved to be decisive in allowing cases D and F to avoid complete failure. Although both projects initially showed signs of failure, case D due to poor tool performance and case F due to limited user adoption, the leadership capabilities of the Project Managers enabled them to promptly recognize the critical issues and implement targeted corrective actions, partially compensating for the shortcomings resulting from the incomplete application of other framework principles.

Conversely, in cases E and G, the lack of sufficiently effective leadership prevented timely and structured interventions, hindering the implementation of appropriate corrective measures and ultimately contributing to the overall failure of the projects.

These findings support the conclusion that, when problems arise due to deviations from the theoretical framework, the leadership of the Project Manager represents a crucial factor in mitigating negative effects, preventing total failure, and, in some cases, enabling the achievement of a partially successful outcome.

Framework timeline analysis

Based on the matrices developed within the *within-case analysis* and *cross-case analysis*, as well as on the testimonies collected and discussed in the previous sections, it is possible to further reflect on the temporal structure of the analysed projects and on their articulation along a reference project timeline.

Identifying a clear temporal sequence through interviews proves to be particularly complex, especially when the interviewer aims to leave a high degree of expressive freedom to the respondents and deliberately avoids guiding or influencing their answers. Moreover, some of the principles on which the framework is based do not have a single, well-defined temporal placement. When present, they tend to manifest across multiple phases of the project rather than being confined to a specific stage. Examples include *"PM leadership and mindset"* and *"Mindset and propensity to change"*, which influence the entire project lifecycle rather than a single operational phase.

Despite these challenges, the analysis and interpretation of the interviewees' statements nonetheless allow for the extraction of a project timeline, albeit in a partial and non-rigidly structured manner. This analysis reveals a general adherence to the sequence proposed by the framework. In the first macro-phase, the project idea and its strategic role within the organization are defined; subsequently, the initiative is presented to top management, which expresses its attitude and level of support toward the project. This is followed by the definition of economic and technical requirements and, once the budget is established and formal approval is obtained, the project proceeds with the involvement of stakeholders and operational staff, marking the beginning of the implementation phase. Finally, a post-deployment phase takes place, characterized by employee training activities and system performance monitoring.

However, the case analysis highlights a significant deviation from the theoretical framework with respect to the placement of the principle *“Create interdisciplinary teams”*. In all analysed cases, requirement definition and budgeting activities are carried out by a project team that is formed only after the initial proposal has been submitted to top management. This difference can be attributed to the fact that requirement definition necessitates the involvement of individuals who are fully aware of the tool’s actual needs, possess in-depth knowledge of the processes affected by the implementation of the AI solution, and have adequate project management expertise.

For this reason, the individuals actively participating in the requirement assessment phase must necessarily be part of the project team, as they hold key technical and managerial competencies. Consequently, in light of the empirical evidence collected, the principle *“Create interdisciplinary teams”* should be positioned immediately before the *“Requirement assessment”* phase, in order to ensure greater coherence between the framework and the interviewees’ testimonies.

4 Conclusion

4.1 Research summary and results

This thesis aimed to analyse, empirically validate, and, where necessary, revise a theoretical framework designed to support the implementation of artificial intelligence projects in the supply chain domain. The analysed framework, proposed in the study *"What could go wrong? Unlocking AI Potential in Supply Chain Management: Design Principles and Best Practices"*, is based on the identification and structuring of the main Critical Success Factors (CSFs) emerging from the literature. These factors are organized into principles and conceptual pillars intended to guide the development and adoption of AI solutions within complex organizational contexts.

To assess the robustness and practical applicability of the framework, the research adopted a qualitative approach based on the analysis of seven case studies, collected through interviews with professionals directly involved in AI projects along the supply chain. The analysis was structured according to a dual perspective: a within-case analysis, aimed at examining each case in depth individually, and a cross-case analysis, focused on systematically comparing the cases in order to identify recurring patterns, similarities, and significant differences.

Overall, the findings indicate a strong empirical alignment with the theoretical framework, confirming the relevance of many of the principles identified in the literature as key factors for the success of artificial intelligence projects. Several principles were consistently applied across the analysed cases, suggesting that they represent well-established and widely recognized elements in project practice. At the same time, the analysis of principles characterized by greater heterogeneity revealed that their partial or missing implementation is often associated with operational inefficiencies, delays, or adoption challenges, in line with theoretical expectations. These results provide additional empirical support for the validity of the framework and further strengthen the link between theory and practice.

Alongside these confirming elements, the research also highlighted two main areas of misalignment with respect to the original theoretical formulation of the framework. The first concerns the "Explainable and Transparent AI" pillar, which was not meaningfully adopted in any of the analysed cases. In light of this evidence, this pillar was reinterpreted not as a strictly enabling prerequisite, but rather as a facilitating element, whose adoption may enhance project effectiveness but does not appear to be essential in the initial implementation phases.

The second significant contribution of this thesis relates to the temporal structure of AI projects(Figure4.1). The analysis of interview data consistently shows that the definition of technical and economic requirements requires the presence of an already established project team with interdisciplinary competencies. Consequently, the principle “Create interdisciplinary teams” appears to be more coherently positioned prior to the “Resource assessment” phase, suggesting a revision of the project timeline proposed by the theoretical framework in order to better reflect the dynamics observed in practice.

Overall, this thesis contributes to the existing literature by providing a structured empirical validation of a theoretical framework for AI implementation in supply chain contexts, highlighting its strengths while proposing targeted adjustments grounded in real-world evidence. From a managerial perspective, the findings offer practical guidance for organizations planning to undertake AI projects, emphasizing the importance of a systemic approach that integrates technological, organizational, and cultural dimensions.

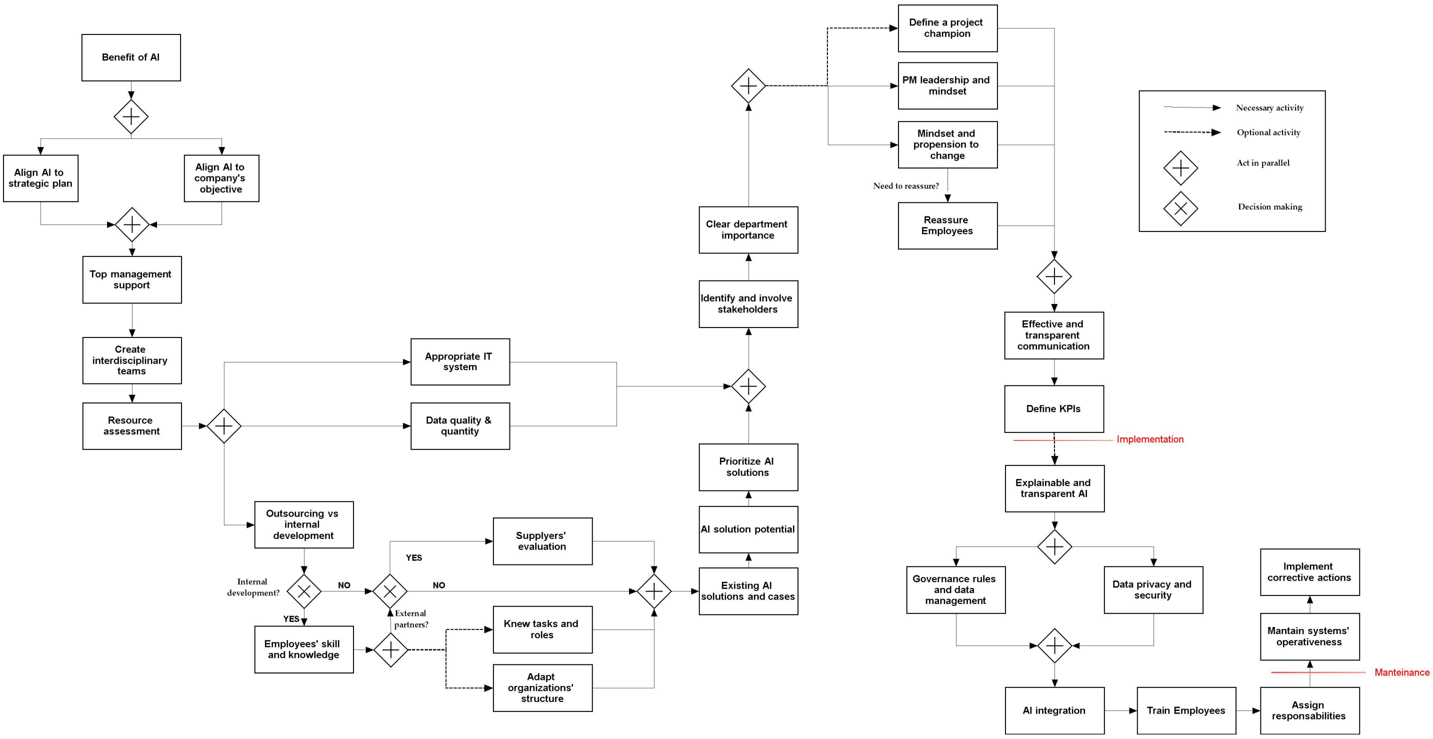


Figure 4.1 Final Framework

4.2 Research limitations

The objective of this thesis was to empirically validate and, where appropriate, revise a theoretical framework through a case study–based approach supported by semi-structured interviews. Although the research produced satisfactory results and contributed to strengthening the robustness and practical relevance of the framework, also in light of the revisions discussed in the previous sections, it is not without limitations. These limitations should be carefully considered when interpreting the findings and assessing their applicability beyond the analysed cases.

The first limitation concerns the generalizability of the results. The empirical analysis was conducted on a sample of seven case studies collected through interviews with professionals involved in AI projects within supply chain contexts. While this number is consistent with established qualitative research practices and allows for an in-depth exploration of complex organizational phenomena, it may not be sufficient to capture the full range of dynamics, challenges, and contextual specificities that can emerge in AI implementation projects across different industries, organizational sizes, or levels of technological maturity. Consequently, the findings should be interpreted as analytically generalizable rather than statistically representative, and caution should be exercised when extending the conclusions to contexts that differ significantly from those investigated in this study.

A second limitation lies in the methodological structure of the analysis. This research relies exclusively on a qualitative approach, based on the collection and interpretation of firsthand testimonies. The interview data were reprocessed, analysed individually through within-case analysis, and subsequently compared through cross-case analysis to identify recurring patterns and divergences using logical and interpretative reasoning. While this approach is particularly well suited to exploring emerging phenomena and understanding underlying mechanisms, it lacks a quantitative or mathematical component capable of providing statistical validation to the observed relationships. As a result, the study does not allow for hypothesis testing or for measuring the strength of causal relationships between specific principles and project outcomes.

Related to this aspect, a further limitation concerns the potential subjectivity of interview-based data. The findings are inherently influenced by the perceptions, experiences, and retrospective interpretations of the interviewees. Although efforts were made to ensure consistency and coherence across cases, individual biases, selective memory, or differences in personal involvement may have affected how certain aspects of the projects were described and evaluated. This limitation is intrinsic to qualitative research designs and further reinforces the importance of triangulating results through complementary methodological approaches.

4.3 Future developments

Despite these limitations, the constraints identified in this study open up several promising and meaningful directions for future research, which could further refine and strengthen the proposed framework. A first and natural extension concerns the expansion of the empirical base. Future studies could include a larger number of case studies, spanning multiple industries, geographical regions, and organizational settings, in order to capture a broader spectrum of implementation contexts. Such an expansion would allow researchers to explore whether the relevance and sequencing of the identified principles remain consistent across different levels of organizational maturity, technological readiness, and supply chain complexity, thereby enhancing the external validity and transferability of the framework.

A second important avenue for future research lies in the integration of quantitative research methods. While the qualitative approach adopted in this thesis proved effective in uncovering underlying mechanisms and contextual dynamics, the combination of qualitative insights with quantitative data, through surveys, structured questionnaires, or statistical modelling, could enable the formulation and testing of specific hypotheses. This mixed-methods approach would allow for the measurement of the relative impact of individual principles or pillars on project outcomes, such as implementation time, cost overruns, system adoption, or performance improvements. In doing so, future research could provide stronger statistical support to the relationships suggested by the framework and increase its analytical rigor.

Furthermore, longitudinal research designs represent a particularly valuable direction for advancing this line of investigation. Observing AI projects over extended periods of time would make it possible to analyse how the importance of specific principles evolves across different phases of the project lifecycle, from ideation and development to deployment and post-implementation optimization. Such an approach could also shed light on delayed effects and learning processes that are difficult to capture through retrospective interviews alone, thereby offering a more dynamic and process-oriented understanding of AI implementation.

Additional research could also focus on context-specific adaptations of the framework, for instance by examining how regulatory environments, data availability, organizational culture, or ethical considerations influence the applicability of certain principles. In particular, further investigation into the role of explainability and transparency in AI systems could clarify under which conditions these aspects shift from being optional facilitators to critical enabling factors, especially in highly regulated or safety-critical supply chain contexts.

In summary, while this thesis provides a structured and empirically grounded contribution to the understanding of AI implementation in supply chain management, its findings should be interpreted as a starting point rather than a definitive conclusion. By addressing the identified limitations through broader empirical samples, methodological diversification, and longitudinal perspectives, future research can further consolidate and extend the proposed framework. Such efforts would not only enhance its theoretical robustness but also contribute to a more comprehensive, nuanced, and actionable understanding of how artificial intelligence can be successfully implemented in complex organizational and supply chain environments.

Appendix

- ## *Within-case analysis*

Appendix A. 1 :Within-case Matrix_1

PROJECT	Organization's strategy	Financial capability	Data & infrastructure	Organization's structure	AI knowledge
A	Digitalization and production efficiency strategy aligned with project objectives. Consolidated understanding of the benefits of AI in manufacturing contexts.	Economic analysis conducted for budgeting purposes. Outsourcing selected for software development.	Data already available within production systems, adapted to the requirements of the solution. IT infrastructure adequate to support the project.	Line parameter setup processes adjusted. Presence of a dedicated digital projects function. Clear responsibilities for performance monitoring and system control.	Multiple AI projects already implemented within the company. Digital function with consolidated experience in AI initiatives. Project prioritized based on expected value creation.
B	Project aligned with efficiency and safety improvement strategies. High awareness of the benefits of AI.	Economic analysis conducted for budgeting purposes. Outsourcing selected for software development.	Data collection through video cameras with significant lead times. IT infrastructure adequate, with the need to integrate video feeds into existing systems.	Definition of new procedures for safety control. Clear responsibilities for system operation and supervision.	Presence of multiple AI projects within the company. Dedicated digital function with consolidated experience. Project prioritization based on expected value.
C	Digitalization and optimization strategy aligned with project objectives. Established knowledge of AI benefits in production.	Economic analysis conducted for budgeting purposes. Presence of an internal team with expertise in developing AI applications.	Data collection was particularly time-consuming. IT infrastructure adequate, with a need to integrate recordings into existing systems.	Processes adapted for integration of new solutions. Team experienced in AI application development. Responsibilities clearly defined for users and performance monitoring.	Several AI and machine vision projects present in the company. Project prioritized based on expected value and fit with the application context.
D	Alignment of the project with the company's strategy and quality standards. Preliminary analysis of AI benefits facilitated by the ongoing digitalization journey.	Financial analysis conducted for budgeting purposes and project approval. Tool development outsourced to external providers.	Extended data collection phase. Insufficient initial quality at go-live, requiring corrective iterations. Overall IT infrastructure adequate to support the project.	Processes adapted to integrate the new tool. The solution supports operators without significantly altering their tasks. Responsibilities clearly defined for system users and performance monitoring.	First machine vision project. High potential impact identified and priority assigned to an AI-based machine vision solution.
E	Part of a corporate digitalization journey focused on improving customer service and reducing costs. The digitalization process increased awareness of the benefits of AI.	Financial and technical analyses were conducted. Software development was outsourced to carefully selected external providers.	Adequate IT system. Data were already available and of good quality, requiring only limited adaptation to the software's needs.	New operating modes and procedures were defined for system users. Personnel were trained on the use of the AI application at the end of the project.	The digitalization path facilitated exposure to AI use cases. Project selection was based on the expected economic and organizational impact, prioritizing the most promising solution.
F	Progetto avviato in un contesto di riduzione degli investimenti. Condotta una fase preliminare di analisi delle potenzialità dell'AI.	Analisi tecnica ed economica svolta per l'approvazione del progetto. Ricorso a fornitori esterni specializzati.	Sistema IT solo parzialmente idoneo. Necessario il supporto di fornitori per gestione dati e sistema. Dati provenienti dai macchinari esistenti, con necessità di adattamento strutturale.	Eliminazione di attività a basso valore aggiunto e riorganizzazione dei processi. Formazione del personale sulle nuove attività e sull'interazione con la soluzione AI.	Analisi dei benefici economici e organizzativi della soluzione AI. Progetto facilitato dalla presenza di un caso comparabile già implementato in azienda.
G	First digitalization project, considered strategic for the company. A thorough preliminary analysis of the benefits and potential of AI was conducted.	A financial analysis was carried out to assess economic feasibility and investment constraints. An enterprise solution provided by specialized external vendors was selected.	Hardware and software were entirely supplied by third parties. Data collection was highly time-consuming, and the underestimation of technical aspects led to significant delays.	Partial impact on operational activities. Personnel were trained on the use of the tool and on how to interact with it.	An analysis of the solution's benefits was performed. Alternative technologies were evaluated, and the option offering the best cost–benefit trade-off was selected.

Appendix A. 2 : Within-case Matrix_2

PROJECT	Employees' management	Top Management	Stakeholders management	Governance & communication	Post deployment
A	High propensity for change and innovation. Strong acceptance of operator-support solutions by personnel. Training provided on tool usage and on new processes for line parameter adjustment.	Absence of a dedicated project champion. Digital team with extensive experience in AI projects. Active role of the project manager in sustaining motivation during final phases. Strong top management support due to the strategic relevance of the project.	Stakeholders identified from the early stages. Project team characterized by a high level of cross-functionality.	Management of strategic data with particular attention to data governance and data privacy aspects.	Definition and monitoring of KPIs. Implementation of structured processes for performance control and system updates.
B	High propensity for change. Involvement of operators and trade union representatives required to ensure proper workforce management.	Absence of a dedicated project champion. Digital team with extensive experience in AI. Project manager effective in actively engaging stakeholders. Initiative promoted by the safety department with the support of top management.	Stakeholders identified and involved during critical phases. Cross-functional team and transparent project communication.	Handling of sensitive data, with strong attention to data governance and data security.	Definition and monitoring of KPIs. Structured processes for performance control and system updates.
C	Employee involvement necessary during the project to improve tool performance and reduce resistance. Operators trained on the AI solution after project completion.	Strong top management support for process optimization projects. Good team management capability. Project champion identifiable as the head of the software development team.	Stakeholders identified and engaged throughout the project. Interfunctional team and transparent communication.	Management of non-sensitive data. Data governance and privacy activities were limited. Black-box solution	Definition and monitoring of KPIs. Implementation of structured processes for results control and system updates.
D	High propensity for change and low invasiveness of the solution. No significant resistance from personnel. Operators trained in the use of the tool.	High strategic relevance and strong top management support. Absence of a project champion with specific experience. Presence of senior managers capable of coordinating stakeholders and maintaining team alignment.	Project scope and roles communicated transparently. Key stakeholders identified and a cross-functional team established.	Management of data considered non-sensitive. Limited data governance and data privacy activities. Black-box solution	Definition of monitoring KPIs and implementation of control and maintenance procedures for the tool.
E	Despite training and feedback collection, adoption of the solution remained limited. Tight timelines did not allow the issue to be adequately addressed during the project.	Project sponsored by top management. A project champion can be identified in the IT manager with greater experience in digital projects. Leadership was not fully effective in managing staff resistance and engaging end users, resulting in limited use of the tool.	Involvement of external stakeholders. Limited internal communication and lack of clarity regarding the roles of different departments.	Handling of confidential and sensitive data, with strong attention to data governance and data privacy aspects.	Definition of monitoring KPIs and implementation of procedures for system control and updates.
F	Forte timore del personale legato alla sicurezza del posto di lavoro e al cambiamento delle mansioni. Tentativi iniziali di gestione delle resistenze non efficaci; per vincoli temporali il progetto è proseguito senza affrontare pienamente il tema.	IT manager identificabile come project champion, con esperienza in progetti analoghi. Leadership poco efficace nella gestione dei timori del personale, con conseguenti ritardi nell'adozione, raggiunta solo dopo mesi di supervisione. Supporto limitato del top management, dovuto alla strategia aziendale, con rallentamenti nella fase di avvio.	Stakeholder identificati e informati sin dalle fasi iniziali. Team di progetto interfunzionale definito dopo l'approvazione. Gestione inadeguata delle resistenze degli operatori.	Data governance e data privacy gestite dall'IT manager con il supporto di un vendor esterno specializzato.	Definizione di KPI di controllo. Periodo iniziale di monitoraggio e correzione delle performance del sistema.
G	Strong resistance from operators. Despite explanatory efforts, traditional tools continued to be preferred.	Absence of a project champion. Leadership was not effective in managing resistance. The initiative was promoted by top management.	A limited number of stakeholders were involved. External vendors were managed effectively, while internal stakeholders (operators) were only partially managed.	Low sensitivity of the data processed. Limited relevance of data governance and data privacy issues.	An initial phase of monitoring and performance adjustment of the tool was initiated.

- ## *Cross-case analysis*

Appendix A. 3 : Cross-case Matrix_1

PROJECT	Organization's Strategy			Financial capability			Data & Infrastructure		
	Benefits of AI adoption	Alignment of AI with business objectives	Alignment of AI with the strategic plan	Resource assessment	Outsourcing vs. internal development	Suppliers' evaluation	Appropriate IT system	AI integration	Data quality and quantity
A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
B	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes	Yes	Not needed	Yes	Yes	Yes
D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
G	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No

Appendix A. 4:Cross.case Matrix_2

PROJECT	Organization's Structure			AI knowledge			Employees' Management			
	Adapt organization's structure	New tasks and roles	Assign responsibilities	Existing AI solutions and cases	AI solutions' potential	Prioritize AI solutions	Employees' skills and knowledge	Train employees	Mindset and propensity to change	Reassure employees
A	Yes	Not needed	Yes	Yes	Yes	Yes	Partial	Yes	Yes	Not needed
B	Yes	Not needed	Yes	Yes	Yes	Yes	Partial	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
D	Yes	Not needed	Yes	No	Yes	Yes	Not needed	Yes	Yes	Not needed
E	Yes	Not needed	Yes	Yes	Yes	Yes	Not needed	Yes	No	No
F	Yes	Not needed	Yes	Yes	Yes	Yes	Not needed	Yes	No	No
G	Yes	Not needed	Yes	No	Yes	Yes	Not needed	Yes	No	No

Appendix A. 5 Cross-case Matrix_3

PROJECT	Top Management			Stakeholders' Management				Governance & Communication			Post-Deployment		
	Top management support	Define a project champion	PM leadership and mindset	Identify and involve stakeholders	Create interdisciplinary teams	Effective and transparent communication	Clear department importance	Governance rules and data management	Data privacy and security	Explainable and transparent AI	Define KPIs	Monitor system operativeness	Implement corrective actions
A	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
B	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Partial	Partial	No	Yes	Yes	Yes
D	Yes	No	Yes	Yes	Yes	Yes	Yes	Partial	Partial	No	Yes	Yes	Yes
E	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
F	No	Yes	Partial	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
G	Yes	No	No	Yes	Partial	Yes	Yes	Partial	Partial	No	Yes	Yes	Yes

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