POLITECNICO DI TORINO
MSc in Engineering and Management

An Artificial Intelligence Framework for Project Initiating

Supervisors

Alberto De Marco

Filippo Maria Ottaviani

Matteo Leschiera

Candidate

Adele Andreetto

November 2025

Index

Abstract

The research draws attention to a question that all companies ask themselves nowadays: "Is it possible, and if so, how can Artificial Intelligence be integrated into the company and its processes?". This thesis specifically deals with the role that Artificial Intelligence could play if integrated correctly within Project Management processes, and it has the aim of exploring how machine learning technologies can support decision-making processes in the early stage of projects. The work arises from the need to identify operational ways to introduce AI tools in organizational contexts, defining a methodological framework that guides their implementation in an effective and sustainable way.

The research path combines a theoretical part, dedicated to the analysis of the fundamentals of artificial intelligence and project management models, with an application part developed in collaboration with Italdesign, a company in the automotive sector. At this stage, operational flows, the structure of business data and the opportunities for integrating AI into request for quotation (RFQ) management were analyzed, identifying the areas with the greatest potential for automation and decision support.

Finally, the thesis proposes a conceptual model for the introduction of AI tools in the project initiating phase, which combines the technological perspective with the organizational one. This approach aims to provide a reference basis for future applications and studies aimed at promoting data-aware and data-centered digital transformation in the field of project management.

Introduction

In recent years, since the advent of Machine Learning algorithms, Artificial Intelligence has become an essential tool in the development of companies, in their industrial transformation and in the race for technologization. The advancement of large companies depends a lot on this technical tool, as it is able to offer support in various areas, automate repetitive tasks and improve productivity. Specifically in the field of project management, the integration of AI represents one of the fundamental obstacles to overcome to achieve a more promising situation, to increase the efficiency, precision and analytical capacity of organizations. This thesis is located precisely in this area of research and, in that perspective, has the objective of developing and testing an artificial intelligence framework applied to the project initiating phase, that is, the preliminary phase of defining and evaluating projects, analyzing the case study of the Italdesign company.

The introduction to the theoretical foundations of work offers an overview of the key concepts of artificial intelligence, machine learning and project management. Specifically, the distinction between generative and non-generative AI was deepened, and it is described how the adoption of these technologies is increasingly redefining business decision-making processes. Secondly, to offer a broad and complete overview of the field of study, the second part of the introductory chapter is dedicated to the principles of project management according to the Project Management Institute (PMI) framework, with particular attention to the triangle of constraints (time, cost, quality) and the project life cycle. The chapter closes with an analysis of the impact of AI on productivity and the role of project managers in a context of increasing automation. In the next chapter, some concrete and already developed and commercialized applications of AI tools are explored along the various phases of the life cycle of a project. Cases and methodologies are analyzed regarding project selection (initiation phase), planning (scheduling and risk management), execution and control, up to the closure phase. Af-

ter the study, it is highlighted how AI, and in particular Generative AI, is transforming project management into an increasingly data-driven process, capable of providing recommendations, predictive analysis and automated reports, while still keeping the role of the project manager central. The third chapter focuses on the role of data, a key element for the effectiveness of any machine learning model. At this stage of the research, the main types of data used in engineering cost estimates, the problems related to their quality, completeness and representativeness, and the importance of the preprocessing and cleaning phases are described. The chapter highlights how the availability of large, clean and diversified datasets is an indispensable condition for obtaining reliable predictive models and how, in engineering realities, data management often represents one of the most complex challenges. In the fourth chapter, the analysis focuses on the corporate context of Italdesign, describing its history, organizational structure and, in particular, the functioning of the Project Management Engineering department. It is illustrated how the pre-initiation phase, which begins with the receipt of requests for offers (RFQ), represents a critical step for company competitiveness. Next, the research question is introduced, which seeks to study if Artificial Intelligence can contribute to enhance the company's cost estimation process. Indeed, the main problem lies in the cost estimation phase, the one preceding the actual start of the project. The complexity and duration of the process, combined with the difficulty of correctly estimating projects characterized by multiple components and variables, make this phase particularly critical. Furthermore, the fact that the estimate is carried out manually and is entrusted exclusively to Project Managers and technical assistants increases the risk of error. An under reporting error can lead to an increase in costs after the event, generating customer dissatisfaction and a loss of credibility for the company; on the contrary, an over reporting can compromise Italdesign's competitiveness, leading to the loss of potential projects to other companies.
The potential contribution of AI lies precisely at this stage: automating the reading and analysis of RFQs to reduce response times, improve the accuracy of estimates and support project managers in preliminary decisions.

Starting from these bases, the research focuses on the case of Italdesign, a company that is a symbol of engineering excellence and Italian automotive design, now part of the Volkswagen group. Through this study, we will try to demonstrate how the introduction of artificial intelligence in project management can generate tangible value, improving the efficiency, timeliness and quality of decisions. The experience gained with Italdesign offers a concrete perspective of how the collaboration between engineering skills and AI tools can lead towards a new vision of project management: more precise, predictive and data-oriented, but always based on the irreplaceable contribution of human intelligence.

Chapter 1

Artificial Intelligence and Project Management: Foundations and Integration

Artificial Intelligence (AI) constitutes one of the most dynamic and transformative fields of contemporary technological innovation, as it aims to develop systems capable of simulating some typical capabilities of human intelligence, such as reasoning, learning, perception, and interaction. Thanks to the integration of sophisticated algorithms and the massive use of data, AI today allows you to automate complex tasks, support real-time decisions, and analyze huge amounts of information with high efficiency. Its applications range from speech and visual recognition to recommended systems, robotics to autonomous vehicles, and healthcare and business management. Current AI implementations rely primarily on machine learning techniques, including supervised, unsupervised, and reinforcement learning, that allow systems to improve their performance through experience (Morales & Escalante, 2022; Alam, 2023). This rapid progress has placed AI at the center of a broad scientific and social debate, highlighting both the opportunities and the ethical and employment challenges related to its large-scale diffusion (Riguzzi, 2006).

The concept of artificial intelligence originated in the 1950s, when John McCarthy officially coined the term 'Artificial Intelligence' in 1956, during a summer seminar at Dartmouth College (Hanover, New Hampshire, USA). The event, which brought together ten US scholars engaged in the study of automate theory, neural networks and intelligence mechanisms, marked the formal beginning of this new area of research. Since then, AI has progressively established itself as an autonomous discipline, while maintaining close interconnections with computer science, mathematics, neuroscience, cognitive science, and philosophy (Feuerriegel et al., 2024).

To understand how Artificial Intelligence works, it is necessary to recall the fundamentals of machine learning (ML), a discipline that studies algorithms capable of improving their performance through experience, that is, by analyzing data.

1.1 An introduction to Artificial Intelligence and Machine Learning

1.1.1 Artificial Intelligence

Artificial Intelligence (AI) is the field of computer science that deals with the design and development of systems capable of performing tasks that, if performed by humans, would require intelligence. Such tasks include, for example, natural language understanding, computer vision, decision-making, problem-solving and learning from experience. The ultimate goal of AI is to build machines that can perceive the environment, reason, learn, and act autonomously or assisted, replicating or expanding human cognitive abilities. AI applications are pervasive today, ranging from healthcare (automatic diagnosis, clinical support) to manufacturing (automation and predictive maintenance), from intelligent transportation to surveillance systems, to personalized education.

In recent years, artificial intelligence has seen extremely rapid development, as much in terms of investments as concrete results. The increase in resources allocated to AI has favored, and at the same time has been encouraged by, important advances in the technological capabilities of intelligent applications. Such advancements are not only about AI in the strict sense, but also related areas such as robotics, sensor systems and digitalization, which allows interconnection between these elements. These innovations are already visible in multiple contexts: think of algorithms capable of exceeding human capabilities in complex strategic games, the development of virtual assistants such as Alexa and Siri, or the new Amazon stores without cash registers and payment staff. Such advances have generated both enthusiasm for the potential positive impact on economic development and concerns about the future of employment, in a context where many activities performed by humans can be automated by algorithms. Some positions are particularly alarmist: for example, Elon Musk has declared that AI poses an existential threat to human civilization (Lana, 2023).

Among the benefits of AI are: improved operational efficiency, automation of complex processes, and the ability to process large volumes of data to support data-driven decisions. However, the adoption of AI also raises significant challenges, including employment risks, algorithmic biases, privacy and security issues, and ethical dilemmas related to the accountability of automated decisions. In light of such considerations, the diffusion of AI requires an integrated approach that combines technological development, ethical regulation, and continuing education to ensure a sustainable and positive impact on society (Pothen, 2022). This rapid diffusion of intelligent technologies fuels a dual feeling in society: on the one hand, the enthusiasm for the potential for economic growth generated by automation, and on the other the concern for the employment and social impact resulting from the substitution of human activities by algorithms (Buchanan, 2005). Sociologically, the emergence of AI offers a unique opportunity to reconsider how we interpret human behavior. Current discussions of expert systems and AI reveal how such technologies are often perceived based on sharp contrasts between human and artificial capabilities. However, these narratives tend to reduce the complexity of sociological knowledge and place technology as an inevitable symbol of progress, often without questioning its social and cultural implications in depth. Some scholars argue that AI should not only be seen as a technological phenomenon, but as an opportunity to rethink the fundamental assumption of sociology: that human behavior is intrinsically 'social' and not merely computational (Riguzzi, 2006).

1.1.2 Machine Learning

Within AI, a central role is played by Machine Learning (ML), which is the dominant approach to developing intelligent systems. ML is a branch of AI that focuses on algorithms capable of learning from data. Instead of being explicitly programmed for each task, these algorithms build mathematical models from past experiences (i.e., data) and use them to make predictions, classifications, or decisions about new data. Machine learning enables systems to progressively improve their performance, sharpening their understanding of the problem due to exposure to increasing amounts of data. Thus, it can be said that AI provides the ambition and goal to build intelligent machines, while machine learning offers the concrete tools to achieve that goal through data analysis and modeling. Thanks to these technologies, AI is transforming strategic sectors such as healthcare, mobility, finance, industry and education, opening up new possibilities for automation, customization and innovation.

ML is divided into four main modalities: supervised, unsupervised, semi-supervised and reinforcement learning (Morales & Escalante, 2022; Alam, 2023).

In supervised learning, training data includes both labeled inputs and outputs, with the goal of building predictive models for new data. This approach is common in classification and regression problems (Sharma et al., 2020; Morales & Escalante, 2022). Among the main supervised learning algorithms, linear regression, Support Vector Machines (SVM) and decision trees stand out.

- Linear regression is one of the simplest and most used algorithms for prediction problems on continuous variables, in which we try to model the linear relationship between a dependent variable and one or more independent variables. This method assumes a direct correlation between input and output, and is widely employed in predictive contexts such as price analysis or sales estimation (Smola & Vishwanathan, 2008).
- Support Vector Machines (SVMs) are more sophisticated algorithms, suitable for both classification and regression problems. The principle behind SVMs is to find an optimal hyperplane that separates the data into different classes, maximizing the distance (margin) between the closest points of the two classes, called support vectors. This approach allows good generalization even in high-dimensional spaces and with complex data sets (Sharma et al., 2020).
- Finally, Decision Trees are hierarchical models in which each internal node represents a decision based on a dataset feature, while leaf nodes represent the predicted output or class. Trees are constructed by recursively subdividing data into more homogeneous subsets, using criteria such as entropy or the Gini index. This method is particularly appreciated for its interpretability and is often used for classification, regression and de-

cision analysis (Sharma et al., 2020).

These three algorithms represent fundamental strategies in supervised learning, each one adapted to specific application contexts based on the nature of the data and analytical objectives.

Unsupervised learning, on the other hand, uses label-free data to identify hidden patterns, for example via clustering techniques, useful for exploring data structure and detecting anomalies. In this context, the algorithm exclusively receives unlabeled inputs and must autonomously locate structures, patterns or correlations within the dataset. The goal is not to predict a known output, but to discover the latent configuration of the data. The most common techniques include clustering, which consists of grouping data into homogeneous sets based on similarity measures and association analysis, which seeks co-occurrence rules between variables. Among the most used algorithms are k-means, self-organizing maps and dimensionality reduction models such as principal component analysis (PCA). Unsupervised learning is critical in scenarios where a labeled data base is not available, such as in exploratory analysis, market segmentation, and anomaly detection (Sharma et al., 2020; Morales & Escalante, 2022). This paradigm also forms the basis for many applications of generative AI, which learn the underlying distribution to data to generate new coherent content (Witten et al., 2017).

Semi-supervised learning is an intermediate modality between supervised and unsupervised learning, where the model is trained on a small set of labeled data and a large amount of unlabeled data. This approach is particularly useful in those contexts where data labelling is found to be expensive or complex, but large volumes of raw data are available. The strategy is to use the information provided by labeled data to guide the interpretation of unlabeled data, improving the generalization of the model. Semi-supervised techniques find application in several domains, including natural language processing, image recognition and fraud detection, where it is often difficult to obtain precise labels for all data (Chapelle et al., 2006). Among the most common methods are label-propagating algorithms, self-training and generative approaches, which estimate the joint distribution of inputs and labels (Zhu, 2005). Semi-supervised learning therefore proves strategic to optimise the use of available data, maintaining a good balance between accuracy and computational costs. Furthermore, with the advent of deep learning, hybrid models have emerged capable of integrating deep neural networks with semi-supervised strategies, further expanding their potential (Kingma, Mohamed, et al., 2014).

Reinforcement learning is a form of machine learning inspired by the cognitive processes of behavioral learning that is grounded in the interaction between an agent and the environment: the agent receives rewards or penalties and learns strategies to maximize expected reward (Morales & Escalante, 2022). The goal of the agent is to learn an optimal policy that maximizes the expected cumulative reward over time. Unlike supervised learning, there are no explicit labels for every input; instead, the agent must learn through experience, exploring the environment and evaluating the effectiveness of the actions taken. Techniques such as Q-learning, policy gradient methods and actor-critic algorithms are among the most common in RL. This approach proves particularly effective in dynamic and complex contexts, such as robotics, industrial control, strategic games and management of financial portfolios. Furthermore, RL is increasingly integrated with deep learning models (deep reinforcement learning), expanding its decision-making capabilities in high-dimensional environments (Morales & Escalante, 2022). Reinforcement learning, however, poses relevant challenges, such as the trade-off between exploration and exploitation and the appropriate definition of the reward function, which are fundamental for successful training (Sutton & Barto, 2018).

Furthermore, in the field of artificial intelligence and data analysis, it is essential to distinguish between descriptive, predictive and prescriptive analytics, since each type responds to different information objectives and makes use of specific algorithmic techniques.

- Descriptive analysis focuses on the interpretation of historical data, in order to understand what happened and identify patterns or trends. It mainly makes use of clustering and dimensionality reduction algorithms, including k-means, used to group similar data and identify significant segments within complex datasets (Wang et al., 2025).

- Predictive analysis instead aims to predict future events or behaviors based on historical and current data. Among the most widespread algorithms in this field is regression analysis, with models such as linear regression or more complex algorithms such as Deep Neural Networks, which allow capturing non-linear relationships in data (Alam, 2023). These models are widely used, for example, to predict market demand, credit risk or predictive maintenance.

- Finally, prescriptive analysis goes beyond prediction, proposing optimal actions to address future scenarios, taking into account constraints, objectives and available resources. This form of analysis is based on optimization models and decision algorithms, among which reinforcement learning stands out, where an agent learns optimal strategies by interacting with the environment and maximizing a reward function (Morales & Escalante, 2022). Such techniques are particularly effective in the dynamic management of complex systems, such as logistics, finance or autonomous robotics.

1.1.3 Generative and non-generative AI

Current AI systems are mainly divided into two broad categories: generative AI and non-generative AI. Both share a mathematical basis grounded in probability and learning from data, but differ in ability, architecture, and application domains. Understanding these differences is crucial to assessing the impact of technology on the economy, work and society.

Generative AI is transversally placed compared to the previously mentioned paradigms, being able to be trained with both unsupervised and semi-supervised data, to learn complex distributions and generate new coherent data.
To work at its best, Generative AI is mainly based on Deep Learning algorithms, a subfield of machine learning that represents a paradigm of great impact in the field of Artificial Intelligence, as it exploits deep artificial neural networks, composed of numerous layers, to extract complex hierarchical representations from data. This approach has achieved extraordinary results in multiple generative activities thanks to its ability to model nonlinear relationships and intricate patterns in data. Among the most advanced generative models we find Variational Autoencoders (VAE), Generative Adversarial Networks (GAN) and Transformers, effective tools for creating high-quality content in various application areas (Goodfellow et al., 2014)).

- Variational Auto Encoders (VAE)

  VAEs are unsupervised learning models that have found wide use within GenAI. They compress the data into a compact latent space, then convert it back into new samples through a decoding process. These models are found to be effective in tasks such as synthetic data generation, anomaly detection and automatic feature extraction (Kingma & Welling, 2013). The ability of VAEs to identify underlying patterns and generate unpublished data makes them valuable tools in areas ranging from image processing to automatic natural language understanding (Larsen et al., 2016).

- Generative Adversarial Networks (GAN)
  GANs are based on a continuous interaction between two neural networks: the generator, which produces content, and the discriminator, which evaluates the authenticity of the generated content. Such configuration allows iterative learning in which both networks progressively improve their performance. GANs have established themselves for their ability to generate images, expand datasets through data augmentation and carry out stylistic transformations (Goodfellow et al., 2014). Their versatility is demonstrated by applications ranging from digital art to medicine, up to entertainment (Karras et al., 2017).

- Transformer Models
  Transformers, represented by architectures such as GPT (Generative Pre-trained Transformer), have profoundly transformed the field of Natural Language Processing (NLP). These models are based on self-attention mechanisms, which allow you to capture contextual dependencies between words in a text, thus generating coherent and relevant content. Transformers find application in multiple fields, including machine translation, text generation and chatbots, thanks to their ability to produce fluent, human-like natural language (Vaswani et al., 2017; Radford et al., 2019). The revolutionary impact of these models has made Transformers essential tools in contemporary generative technologies.

Generative AI is therefore not limited to mere reproduction, but generates new content, expanding operational possibilities in areas such as the start of the project. However, the adoption of GenAI requires new skills: strategic goal setting, interpretation of probabilistic outputs, assessment of risks and ethical implications (Boakye Acka & Sarkodie, 2024; Project Management Institute, 2024).

Unlike generative AI, non-generative AI focuses on analyzing and interpreting large amounts of data to detect patterns, make predictions, and optimize decisions. This type of AI does not produce new content, but provides support based on existing data. The main techniques are Machine Learning (ML) and Deep Learning (DL), which use probabilistic models to predict outcomes and recommend actions.
Non-generative AI is widely employed in activities such as:

- Pattern recognition (texts, images, sounds)

- Anomaly detection (e.g. financial fraud)
- Personalization (user behavior analysis)
- Operational optimization (e.g. traffic management, supply chain).

A strength of modern non-generative AI is the ability to handle huge datasets, even unlabeled and unstructured ones, making it particularly suitable for big data analysis (Filippucci et al., 2024).

1.2 An introduction to Project Management

In today's context, characterized by rapid technological evolutions and growing organizational complexity, Project Management takes on a central role, particularly in the field of engineering and innovation. Engineering projects are often complex, expensive and critical, requiring management skills not always included in traditional degree pathways. Project management provides a set of methodological and operational tools to translate ambitious visions into concrete results, enabling organizations to adapt, respond and thrive in dynamic and competitive environments. In particular, these skills make it possible to optimise resource allocation, meet customer expectations, adapt to market changes, manage risks and promote innovation (Weng, 2023; Aggrawal & Dittman, 2023).

The Project Management Institute (PMI) has formalized a global framework for project management, known as the Project Management Body of Knowledge (PMBOK). This framework brings together established processes, terminologies and best practices, dividing them into ten areas of knowledge, including scope, time, cost and quality management. The PMBOK includes 49 operational processes that describe the core tasks to be performed throughout the project lifecycle. It is a flexible and adaptable system, designed to be customized based on the specificities of the project and to evolve in parallel with technological progress. In this context, the integration of emerging technologies such as artificial intelligence –for example via tools such as ChatGPT-4 – opens new perspectives for the improvement of project management processes and results (Weng, 2023).
According to the official definition (Project Management Institute, 2023; Institute of Project Management Ireland, 2024), project management consists of the professional and systematic

application of processes, knowledge and tools aimed at completing a project by efficient use of available resources. A project is defined as a temporary set of activities that produces a useful result upon completion. Project management processes involve skills, finances and tools, applied according to codified methodologies to maximize production efficiency.

1.2.1 Project Management's triangle

One of the founding principles of project management is the so-called "project triangle" or "iron triangle", which represents the basic constraints to which each project is subjected: scope, time and cost. The scope defines what needs to be achieved, i.e. the objectives and deliverables of the project. The time corresponds to the duration assigned to complete the tasks, while the cost represents the overall budget available. These three elements are interdependent: significant changes in one of the three constraints necessarily affect the others, requiring careful planning and control (Asana, 2024).

- Scope

  The scope represents the "scope" of the project in terms of complexity, quality and quantity of the expected deliverables. As the scope increases, the time and resources required for completion increase proportionally. Scope-specific elements include the number of deliverables, expected final quality, operational power (e.g. supported users), and functional complexity. Accurate scope definition is essential to avoid so-called scope creep, or uncontrolled slippage of project objectives.

- Cost

  The cost is not limited to the monetary budget, but includes all the necessary resources: people, tools, materials and infrastructure. The cost covers the number of team members, specific equipment and other strategic resources. Effective budget management is crucial, as unexpected variations (e.g. increased staffing or energy) can significantly alter the project budget.

- Time

  Time measures both the overall duration of the project and the quality of its planning. Key aspects include the timeline, working hours, internal calendars and the number of operational phases. Reducing the budget or broadening the scope requires smart adaptation of deadlines, to balance constraints and ensure delivery on schedule.

The project triangle represents the concept of “triple constraint”: any change to one of the three elements (scope, cost, time) has impacts on the other two. The project manager’s task is to balance these factors, ensuring the quality and implementation of the project within budget and time limits (Asana, 2024).

The wildcard factor: innovation

A key element in improving design efficiency is innovation. The introduction of new technologies, such as AI tools, can optimize costs and reduce time without necessarily altering scope or quality. For example, the adoption of advanced project management software, or the standardization of decision-making processes via predictive models, can increase productivity by reducing the waste of resources. Investing in AI can therefore represent a “wildcard factor” that improves project management without sacrificing quality or value (Asana, 2024).

In the context of project management, AI is establishing itself as a tool for automation, assistance and strengthening decision-making skills. For example, it can be used to generate reports, estimate costs and times, analyze risks, draft documents and support communication between stakeholders (Boakye Acka & Sarkodie, 2024; Project Management Institute Sweden Chapter, 2024). This tripartite division, automation, assistance, enhancement, is useful for assessing the interaction between GenAI and the human, as the complexity of the task increases, the need for human intervention grows (Project Management Institute, 2024). Project management is defined as the structured and professional application of knowledge, tools, techniques, and processes aimed at achieving specific goals within a predetermined set of constraints, typically involving scope, time, and cost. The Project Management Institute (PMI), one of the global reference institutions in this field, defines project management as "the use of experience, knowledge, tools and techniques to carry out a project effectively and efficiently" (Project Management Institute, 2024).

A project, in the proper sense of the discipline, is a set of temporary activities with a specific purpose: to create a unique and valuable product, service or result. Thus, project management is configured as the methodical approach to guide a team towards the completion of a project, making optimal use of available resources –human, material, technological and financial – through systematic processes that aim to maximize production efficiency.

1.2.2 The Project Life Cycle

The life cycle of a project represents the sequence of phases that a project goes through from its conception to its closure. According to the framework proposed by the Project Management Institute and shared by other training bodies such as the Institute of Project Management Ireland, the project life cycle is divided into five main phases: Initiation, Planning, Execution, Monitoring and Control, and Closure.

- The initiation phase marks the formal beginning of the project. It includes setting key objectives, identifying stakeholders and drafting the project charter. The goal is to determine the viability of the project and obtain approval to proceed. In this context, the initial scope is also established and risks and benefits are assessed.

- The planning phase is crucial to the success of the project. It includes the detailed definition of activities, the creation of the Work Breakdown Structure (WBS), time planning (schedules), cost estimation and the preparation of a risk management plan. This phase leads to the production of the project management plan, the guiding document that regulates all subsequent activities.

- During execution, the project gets to the heart of things: resources are allocated, deliverables are produced, and the team performs the tasks in the plan. Effective communication between stakeholders and careful team management is crucial. In parallel, plans for quality, supplier management and resource allocation are implemented.

- The Monitoring and Controlling phase, often carried out in parallel with execution, aims to ensure that the project proceeds as planned. Progress is monitored, performance against time, cost and quality indicators is assessed, and corrective actions are implemented when necessary. Tools such as Earned Value Management (EVM) are used to control deviations from the plan and prevent delays and budget overruns.

- Finally, the closure phase includes the finalization of all project activities, the release of resources, the verification of stakeholder satisfaction and the formalization of the acceptance of deliverables. It is also the moment in which lessons learned are conducted and the knowledge acquired for future projects is documented. Effective closure is key to assessing overall success and consolidating organisational knowledge.

In conclusion, project management is not simply a series of tools or techniques, but a strategic discipline that integrates management skills, methodologies and relational approaches. It is a key factor in transforming ideas into concrete and measurable results, and today constitutes an essential lever for innovation, efficiency and competitiveness in organizations (Weng, 2023; Project Management Institute Sweden Chapter, 2024; Project Management Institute, 2024).

1.2.3 Elements of project planning

Work breakdown Structure (WBS) : Within project management, the Work Breakdown Structure (WBS) constitutes a fundamental tool for planning, monitoring and controlling activities. It represents a hierarchical breakdown of the work to be carried out, oriented towards deliverables, i.e. the concrete results that the project must produce. The definition provided by the Project Management Body of Knowledge (PMBOK) describes the WBS as a "hierarchical decomposition of the total scope of work to be carried out by the project team, to achieve the project objectives and generate the required deliverables" (Alutbi, 2020).

The WBS allows a complex project to be divided into manageable components, facilitating the assignment of responsibilities, cost estimation, time scheduling and reporting of work hours. Each element of the WBS can represent a product, data, service or combination of these, and is defined so that it can be described, measured, monitored and managed independently. A well-designed WBS is definable, estimable, measurable, integrable and adaptable, and allows you to trace the links between functional requirements and operational activities, making the management of complex projects more efficient. There are different types of WBS, which are distinguished based on the decomposition criterion chosen. The main ones are:

- phase-based WBS, which structures work based on phases of the project life cycle (for example: analysis, design, implementation);
- the WBS for deliverable (deliverable-based), which focuses on the tangible results to be produced;
- the WBS by responsibility (responsibility-based), which breaks down activities according to the organizational units involved (for example, by departments or teams).

The importance of the WBS lies in its ability to provide an overview of the project, while maintaining a high level of operational detail. It is used not only as a guide for work planning, but also as a basis for the development of cost structures, quality plans, and progress criteria. Furthermore, it represents an effective communication tool, as it provides a common language between stakeholders, sponsors and project teams.

Cost Breakdown Structure (CBS) : Within the set of structural tools employed in project management, the Cost Breakdown Structure (CBS) represents a fundamental element for the planning, monitoring and economic control of a project. It consists of a hierarchical breakdown of the costs associated with the different components of the project, structured to reflect the Work Breakdown Structure (WBS) and, in many cases, also the Organizational Breakdown Structure (OBS). Each element of the CBS represents a coherent and aggregable subset of the total costs of the project, thus allowing detailed visibility of direct and indirect costs related to specific phases, deliverables, or organizational units. The CBS has the objective of associating measurable economic values with the activities and work packages defined in the WBS, facilitating the definition of budgets, the allocation of financial resources and the subsequent control of expenditures. It is used as a basis for the construction of the project estimate, for the drafting of the baseline cost plan and for the continuous comparison between planned costs and actual costs. Its modular structure also allows integration with corporate accounting systems and project management software. In addition, the CBS supports the early identification of economic variances, allowing the project manager to implement corrective strategies and maintain financial control. A well-constructed CBS, therefore, not only fosters transparency in the management of funds, but also helps to ensure that the project is completed within budget constraints, improving the forecasting and profitability of the project initiative (Alutbi, 2020).

Procurement management is the element of project management concerned with acquiring the goods, services, or external resources needed to complete the project. Not all projects require procurement (if all work is done in-house with internal resources), but many projects do rely on third-party suppliers or contractors for certain components or expertise. For example, a construction project might need to procure raw materials like steel or concrete, or an IT project might outsource the development of a particular software module. Project managers must plan and oversee the procurement process to ensure that what is needed is obtained on time and within budget, and that it meets the project's specifications.
A fundamental step in project procurement is identifying what needs to be procured and when.

This is often documented in a procurement plan or procurement management section of the project plan. Once the needs are identified, the project team (often with a procurement department) will reach out to potential sellers or vendors. Here, standard procurement instruments come into play, such as RFIs, RFPs, and RFQs:

- An RFI (Request for Information) is generally used to gather information about products or services from potential suppliers when the project team is not yet ready to request a formal bid.
- An RFP (Request for Proposal) is a detailed request asking suppliers to propose solutions or services to meet a particular project need, including how they would do the work and at what cost.
- An RFQ (Request for Quotation) is typically a more specific solicitation focused on obtaining price quotes for a well-defined product or service.

In the context of daily project management, RFQs are used when the project needs to purchase commodity items or standardized services and the primary selection criterion is price. An RFQ invites suppliers to submit a price quotation for supplying certain goods or services as specified in a statement of work or item description (Project Management Institute, 2017). For example, if a project requires 100 new laptops for the team, the project manager might issue an RFQ to multiple vendors listing the required specifications of the laptops; vendors will reply with their price quotes, and the project can then choose the lowest bid (or the best value considering price and other factors like delivery time). RFQs streamline procurement when the scope of what is needed is clear and can be described in detail.

Project managers work closely with procurement specialists to evaluate bids or quotes that come in response to RFPs/RFQs. On a daily basis, this might include reviewing proposals, comparing prices and terms, negotiating with preferred vendors, or clarifying requirements. Once a vendor is selected, the procurement process leads to the award of a contract. The project manager must then manage these contracts throughout the project, ensuring that vendors deliver on time, within budget, and to the required quality standards. This involves maintaining communication with suppliers, monitoring their performance, and processing any required payments or change orders. Procurement also intersects with risk management (even though we do not cover risk in detail here): for instance, choosing a reliable vendor and having backup

options can mitigate the risk of supplier nonperformance.
In general, procurement management ensures that the project can obtain the external resources it needs. Tools such as RFQs and RFPs are everyday instruments for project managers when dealing with external market interactions. By following a structured procurement process, from need identification and solicitation (RFQ/RFP) to vendor selection and contract administration, project managers help secure timely and cost-effective input for their projects (Kerzner, 2022). In addition, establishing clear terms (through contracts) and maintaining good supplier relationships is important to avoid delays or disputes that could jeopardize the project timeline or budget.

1.2.4 The impact of AI on productivity

Artificial intelligence (AI) played an important role in the evolution of contemporary economic productivity, establishing itself as a general purpose technology (General Purpose Technology, GPT) with transformative potentials on a global scale. Unlike historical GPTs, such as electricity or the internet, AI possesses peculiar characteristics: the ability to operate autonomously and self-improve through learning from data. These properties allow it not only to perform complex tasks, but also to accelerate innovation, improving the efficiency of both businesses and economic systems as a whole (Lorenz et al., 2023).

In the business context, AI is interpreted as a new production function, combining intangible inputs, such as data, skills, and software, with digital and computational infrastructure to generate high value-added outputs, including forecasts, optimizations, recommendations, and generated content (Generative AI). The adoption of AI allows companies to automate repetitive tasks, improve decision-making processes thanks to real-time data, and optimize the use of resources, with measurable impacts on productivity. Empirical research has highlighted that generative AI tools such as ChatGPT or GitHub Copilot can increase individual productivity by between 10% and 56%, depending on the type of activity and the level of experience of workers, making them particularly advantageous for less experienced profiles.
However, if the microeconomic benefits appear evident, the aggregate effect of AI on macroeconomic productivity remains uncertain. Currently, AI adoption is still limited, involving less than 10% of businesses, and is heavily concentrated in a few large technology companies and knowledge-intensive sectors, such as finance and information technology. This concentration

can generate increasing performance gaps between leading firms and those that remain on the margins of innovation. Furthermore, AI could accentuate phenomena such as the so-called "Baumol disease", where employment shifts to low-productivity sectors, reducing overall efficiency gains.

On the work front, AI is configured as a dual-use technology: it can replace some human tasks or complement them. If used to automate, it tends to reduce labor demand; if used as support, it can enhance workers' cognitive and operational skills, generating new demand for skills. In high-exposure sectors, such as legal advice and finance, AI predominantly threatens entry positions, while reinforcing the value of expert profiles. Enterprises, rather than drastically reducing employment, restructure organisational processes, shifting workers to non-automatable and more value-added oriented activities.
However, the spread of AI encounters significant obstacles. Among the main barriers to adoption are high infrastructure costs, the scarcity of specialist skills –only 0.34% of the workforce has AI skills – and technological concentration: the top ten global companies absorb over 50% of opportunities for AI-related jobs. This risks accentuating the market power of big tech, limiting competition and hindering the fair diffusion of innovations.

Finally, AI poses social challenges and systemic risks, ranging from misinformation to loss of privacy, to ethical and political concerns, such as loss of human control over decision-making processes. To address these risks, the OECD suggests integrated policies that promote equitable access to technology, investments in training and retraining, and ethical governance of AI, based on transparency and algorithm control and auditing mechanisms. In conclusion, AI represents a strategic lever for global productivity, but its benefits will depend on the collective ability to govern its adoption in an inclusive, equitable and sustainable way. Only with effective public policies will it be possible to balance automation and enhancement of human capital, ensuring that AI development contributes to shared economic and social well-being (Lorenz et al., 2023).

Chapter 2

AI Tools for Project Management

In recent decades, artificial intelligence (AI) has emerged as a transformative force in multiple industries, including engineering and project management. Although, interest in AI is not new, just think of its first applications discussed in the early 1990's (Leitch, 1992); it is thanks to the advent of Generative AI that we are now witnessing a significant acceleration of its adoption in the context of Project Management.
The increasing complexity of projects, the pressure to optimize resources and timeframes, and the enormous amount of data generated in the planning and execution phases make the integration of AI increasingly strategic. In particular, GenAI is transforming the way projects are conceived, managed and delivered, offering tools capable of generating documents, forecasts, plans, communications and analyses autonomously or assisted by humans.

The adoption of AI has been consolidated especially in the intermediate stages of the project life cycle (planning, execution and monitoring) through activities such as:

- automation of repetitive tasks
- decision-making support
- risk management and predictive analytics
- reporting and generation of documentation
- assistance in communicating with stakeholders and suppliers (Mangal, 2023; Project Management Institute Sweden Chapter, 2024).

In this context, AI does not replace the project manager, but enhances his capabilities, as also stated by the Project Management Institute "Project managers who know how to use AI will replace those who do not know how to use it" (Project Management Institute Sweden Chapter, 2024). The role of the professional evolves, requiring hybrid skills that include both traditional management and communication skills, the so-called "power skills", and growing digital literacy and knowledge of AI technologies (Project Management Institute, 2023).

Process - How to Implement AI in PM in an Organization

The introduction of artificial intelligence (AI) in project management involves numerous challenges, so that it is not uncommon for AI projects to fail in the implementation phase. The main obstacle lies in the very nature of the projects: they are temporary, unique and often do not produce sufficient amounts of structured data to feed a machine learning model. It follows that crucial decisions remain largely entrusted to the experience and intuition of the project manager, elements that are difficult to transfer to an algorithm. This limits the immediate applicability of AI, while leaving room for significant opportunities in specific areas of the project life cycle.

The causes of failure of AI projects are multiple and can arise from technical (lack of data or infrastructure), organizational (lack of clear governance) or cultural (resistance to change) obstacles.

To improve success rates, it is necessary to adopt structured approaches that allow use cases to be correctly identified, prioritized and implemented. Within this framework, three methodological tools are particularly effective:

1. Task-based approach, useful for identifying processes and activities in which AI can generate value.

2. Weighted Shortest Job First (WSJF), for prioritization of identified use cases.

3. CRISP-DM (Cross Industry Standard Process for Data Mining), as a reference methodology for the implementation and lifecycle management of AI solutions.

A crucial aspect is the collaboration between project teams and data science teams. The former possess the domain expertise necessary to identify the areas with the greatest added value, while the latter guarantee technical feasibility and the definition of realistic expectations.

Identification of tasks with high AI potential

The activity of a project manager can be broken down into elementary tasks, which form the basis for the selection of use cases. These can be classified, in collaboration with data scientists, distinguishing between:

- Use cases for Machine Learning (ML), suitable for forecasting and classification tasks on structured data (e.g. costs, times, performance).
- Use cases for Generative AI (GenAI), suitable for content production, document synthesis and support for qualitative reasoning on unstructured data (e.g. reports, presentations, emails).

In general, a task is well suited to automation via AI if:

- it has a large and accessible database;
- its process knowledge is well documented;
- it does not require high interpretability of decisions;
- the error has no critical consequences for the success of the project.

To determine which tasks to implement first, Weighted Shortest Job First (WSJF), originally designed for Agile environments, is adopted. Adaptation to AI project management involves the following wording:

$$WSJF = \frac{\text{Project Impact} + \text{Data Availability}}{\text{Technical Complexity} + \text{Data Requirements}}, \tag{2.1}$$

where:

$ProjectImpact = FinancialImpact + TimeImpact + RiskImpact$

- Financial Impact: economic relevance of the task (contingent costs or revenues).
- Time Impact: Amount of time absorbed by the team on the task.

- Risk Impact: Degree of risk (financial, technical or related to information uncertainty) mitigatable with AI.

$$TaskSize = TechnicalComplexity + DataRequirements$$

- Technical Complexity: technical difficulty of implementation (low if solutions exist "off-the-shelf", high if ad hoc development is needed).

- Data Requirements: quantity and quality of data required.

In practice, each parameter is evaluated by the project team and the data team on a discrete scale (eg. 1 to 3). This allows you to calculate a WSJF score for each task and generate a priority ranking. Higher scoring tasks are those that combine greater potential impact and lower implementation costs, and can therefore be implemented.

This chapter will explore the benefits, challenges and concrete applications of AI in Project Management. Starting from the analysis of the main functions enabled, we will come to consider future scenarios and conscious adoption strategies, with the aim of highlighting how artificial intelligence can contribute to create value, improve competitiveness and face the strategic challenges of modern projects.

2.1 AI Decision Support in Project Initiation (Project Selection Phase)

One critical early-phase activity in project management is project selection, deciding which projects to pursue from a portfolio of proposals. AI-based decision support systems have been developed to aid project managers and stakeholders during the Initiation phase by evaluating project proposals against success criteria. For example, Costantino et al. (2015) developed an artificial neural network (ANN) model to support project portfolio selection, using Critical Success Factors as input criteria. Their system was trained on historical project data to predict the likely success or risk of new project proposals, effectively prioritizing projects for investment. By learning from past project outcomes, such an AI tool can objectively assess complex combinations of factors (budget, timeline, team experience, etc.) that influence project success. This assists decision-makers during initiation in choosing projects that align with strategic goals and have higher probability of success. In practice, using an AI recommender in project selection can reduce human bias and process large amounts of proposal data quickly (Odejide & Edunjobi, 2024). The ANN-based tool by Costantino et al. (2015) exemplifies how AI can augment the project chartering and selection process, making initiation more data-driven. Notably, such tools are typically used before formal planning begins, they inform which projects should be initiated.

AI can also assist initiation by analyzing feasibility and preliminary risks. For instance, modern project management platforms might leverage machine learning to predict feasibility or perform initial risk screening on project ideas. Some research prototypes use Natural Language Processing (NLP) to evaluate early project documents or business cases. While still experimental, these AI features in Initiation phase help project managers justify and scope projects with greater confidence (Shamim, 2024). Overall, AI tools in project initiation aim to support strategic decision-making – selecting the right projects and defining them clearly – by learning from historical project data and criteria.

2.2 AI Tools for Project Planning (Scheduling and Risk Planning)

The Planning phase benefits extensively from AI techniques. Project planning involves defining activities, estimating durations, sequencing tasks, allocating resources, and identifying risks, all areas where AI can improve accuracy and efficiency. One key planning activity is project scheduling, and researchers have created AI-driven scheduling tools to aid project managers in building optimal project timelines. These tools often employ algorithms such as evolutionary computation, machine learning, or even generative AI to handle the complex constraints of scheduling. For example, Bahroun et al. (2023) conducted a systematic review and found that numerous AI techniques – including evolutionary algorithms (like genetic algorithms), neural networks, and reinforcement learning, have been applied to project scheduling problems. These AI methods can optimize schedules by automatically exploring countless task sequences and resource allocations under given constraints. In fact, AI-based scheduling systems are capable of accounting for uncertainty and dynamically adjusting plans: Bahroun et al. (2023) note that modern neural network models help handle uncertainty and support real-time decision-making in scheduling by integrating risk factors. Such tools are used in the Planning phase to generate baseline schedules that minimize project duration or cost while respecting dependencies and resource limits. An example in practice is the use of generative scheduling platforms (often powered by AI) that can simulate millions of scheduling scenarios. For example, ALICE, an AI-driven construction scheduling tool, automatically creates optimized construction project schedules by exploring numerous sequencing possibilities. By leveraging AI, project managers can evaluate various "what-if" scenarios rapidly during planning, something that would be infeasible manually.

Beyond scheduling, AI is also being leveraged for risk planning. Identifying potential risks early in the project and planning mitigation strategies is a core part of project planning. Traditional risk identification relies on expert brainstorming and historical checklists, but AI can augment this by analyzing large knowledge bases of past projects. An illustrative tool in this domain was developed by Zou et al. (2017), who created an NLP-based system to retrieve similar past project cases to inform risk management in new projects. Their tool scans textual databases of project reports and lessons learned to find projects with profiles comparable to the current project, and then extracts what risks were encountered. By using natural language processing to understand project descriptions and outcomes, the system can suggest "hidden" risks that a manager might overlook, along with proven mitigation measures from past cases (Zou et al., 2017). This AI assistant for risk identification is typically used in the Planning phase (during risk management planning), helping project managers develop more comprehensive risk registers and mitigation plans. With AI's ability to mine historical data, planners gain a broader perspective on what could go wrong, leading to more robust risk planning.

Another task of planning enhanced by AI is the estimation of efforts and costs. Although not a single 'tool' per se, research has shown that machine learning models (such as regression algorithms or ANN) can predict project effort and cost with greater precision by learning from historical project metrics. For example, Wauters & Vanhoucke (2016) compared several AI methods for project duration forecasting and found that these methods can significantly improve the accuracy of schedule estimates in the planning stage. Reliable estimates are crucial in planning for setting realistic schedules and budgets; AI assists by detecting patterns in past estimation data (e.g. underestimation biases) and adjusting new project estimates accordingly. In summary, AI planning tools, from intelligent schedulers to risk analysis assistants – are used in the planning phase to create more optimized and foresighted project plans.

2.3 AI Tools for Project Execution, Monitoring and Control

During the Execution phase (and the overlapping Monitoring & Control phase), project managers must track progress, manage team communications, and ensure that the project stays on course. AI tools in this domain act as intelligent assistants that automate routine monitoring tasks, provide predictive insights, and facilitate communication between stakeholders. One concrete example is the Project Reporting Management System (PRMS) developed by Tan et al. (2021), a prototype tool that automates project progress reporting using AI. PRMS is a web-based system that allows team members (for example, researchers in the prototype case) to submit periodic progress reports online; then it uses machine learning and natural language processing to summarize and consolidate these reports into high-level summaries for management (Tan et al., 2021). Essentially, PRMS autogenerates an executive summary by ranking sentences and extracting the most important information from detailed status reports. This significantly reduces the manual effort that a project manager spends in collating updates and preparing status reports. PRMS also automates the notification and deadline tracking for report submissions. Using AI-based text summarization, the tool helps during execution / monitoring by providing timely synthesized updates on project progress (Tan et al., 2021). This allows the project manager and stakeholders to quickly grasp the status of the project and focus on issues or exceptions rather than wading through long documents.

Another class of AI tools in execution are predictive analytics systems that forecast project performance metrics in real time. These tools often use machine learning models trained on historical project performance data to predict outcomes like final project duration, cost at completion, or upcoming bottlenecks. For example, AI-driven forecasting models can continuously analyze current project performance (e.g. task completion rates, burn-down charts, earned value metrics) and alert managers if the project is likely to slip behind schedule or overrun budget. In the project control literature, methods such as support vector machines or LSTM neural networks have been used to improve the accuracy of Earned Value Management forecasts mid-project. Such AI systems are typically integrated into project management software during the Monitoring and Control phase. They serve as an early warning mechanism, if an algorithm predicts a schedule delay based on current trends, the project manager can take corrective action (reallocate resources, crash the schedule, etc.) proactively. Research byWauters & Vanhoucke (2016), for instance, showed that AI methods could outperform traditional statistical techniques in predicting project duration at various checkpoints. By using these predictions, project managers in Execution can focus attention on troubled tasks or adjust scope and resources to keep the project on track.

AI also enhances communication and decision support during execution. AI chatbots and virtual assistants are increasingly integrated with team collaboration tools (like Slack, Teams, or project management platforms) to facilitate real-time communication and information retrieval. Shamim (2024) notes that AI-driven chatbots can provide 24/7 assistance to project teams by answering queries about project data, sending automated reminders, and even helping coordinate tasks. For example, a chatbot in a project workspace can be asked "What's the status of Task X?" and it will instantly query the project database and respond with the latest update, or it might proactively notify the team about an upcoming deadline and outstanding tasks. These AI assistants leverage NLP to understand user questions and connect to project information, acting as always-available junior project coordinators. By doing so, they reduce communication lags and ensure team members have up-to-date information, thereby improving execution efficiency. Indeed, Salimimoghadam et al. (2025) highlight that such chatbot tools can enhance stakeholder engagement by providing quick, on-demand project updates and facilitating smoother collaboration.

During Monitoring & Control, AI tools can also help with quality and risk monitoring. Beyond the planning-stage risk identification mentioned earlier, execution-phase AI systems monitor ongoing activities for emerging risks. For instance, some experimental tools use pattern recognition on project data (like issue logs or team messages) to detect early signs of trouble – perhaps an increasing frequency of certain error reports could trigger an AI to flag a potential quality issue. In safety-critical projects (e.g. construction or engineering), computer vision AI is used to monitor sites for safety compliance during execution (e.g. automatically checking if workers are wearing protective equipment in real-time video feeds), although that crosses into specialized domains. Overall, Execution and Monitoring phases benefit from AI through automation of routine oversight (status reporting, reminders), predictive insights (forecasts and anomaly detection), and enhanced communication (intelligent assistants), all of which free the project manager to focus on high-level decision-making and leadership tasks.

2.4 AI Support for Project Closure and Learning

The Closure phase of a project, which involves closing contracts, releasing resources, and capturing lessons learned, is an emerging frontier for AI tools. While AI's use in closure is not as developed as in earlier phases, there are noteworthy efforts to leverage AI for lessons learned analysis. At project closure, teams often document what went well or poorly to inform future projects. AI can help transform this typically static repository of lessons into actionable intelligence. For example, some project knowledge management tools now include AI-driven recommendation systems that analyze a database of past project lessons and automatically suggest relevant lessons learned for new projects or upcoming phases (Centric Consulting, 2023). An AI agent can sift through thousands of past reports to find patterns, such as repeated causes of delay or effective risk mitigations, and present the most pertinent insights to the project manager (Forbes Insights, 2025). By doing so, AI turns "past mistakes into risk intelligence," helping organizations avoid repeating errors (English, 2025). Although research and adoption in this area are still nascent, the Closure phase stands to gain from AI through improved institutional learning. In essence, AI tools can ensure that the hard-won knowledge from completed projects is distilled and fed forward into the initiation and planning of subsequent projects, closing the loop of continuous improvement.

It's worth noting that AI tools for closure must overcome challenges like unstructured data (lessons are often text narratives) and organizational resistance to fully utilizing lessons learned. However, preliminary industry reports suggest that when AI is applied to mine lessons learned, it can identify hidden risk factors and propose mitigation strategies for future projects (English, 2025). This indicates strong potential for AI-driven knowledge management tools to become a standard part of project closure in the near future.

Chapter 3

The role of data

Data plays a fundamental role in machine learning (ML), as it forms the basis on which algorithms learn and make decisions. The quality, quantity and representativeness of data directly affect the performance of predictive models. In particular, the data powers ML's algorithms, allowing them to identify patterns, make predictions and make autonomous decisions. However, it is essential that the data is accurate, complete and free of bias to ensure reliable results. A low-quality dataset can lead to inaccurate or unfair patterns. Data is at the heart of machine learning: without high-quality data, even the most sophisticated algorithms cannot function effectively. In fact, modern AI applications require large quantities of training and test data, and the success of AI models depends heavily on the quality, quantity, and representativeness of the data on which they are trained (Anolytics, 2024; Mohammed et al., 2025). In the context of engineering cost estimation, this means ML models learn cost-driving patterns (e.g. how project features relate to cost) directly from historical project data and other related datasets. If those data are lacking or flawed, the resulting cost predictions will suffer. The old adage "garbage in, garbage out" is especially pertinent: poor data quality can lead to unreliable models and ultimately poor decisions. Harvard Business Review (2025) aptly noted that poor data quality is enemy number one for machine learning, since bad data can mislead models both during training and when making new predictions. In cost estimation, data provides the empirical foundation upon which AI algorithms build predictive cost models. Historical project cost data, when properly collected and curated, becomes a reliable foundation for future estimates (ProjStream, 2024). AI/ML systems excel at analyzing vast datasets far beyond what human estimators can handle, uncovering hidden trends and correlations in project costs. These systems can rapidly ingest decades of past project data and learn the complex, non-linear relationships between cost and project attributes. In essence, data enables AI to move cost estimation from intuitive guesswork to a data-driven science, automating the extraction of insights that would be impossible to obtain manually (Shamim et al., 2025). However, this power is only realized if the underlying data is trustworthy. Clean, well-organized data essentially teaches the AI model how to estimate costs; if that "teaching material" is incomplete or biased, the model will reflect those shortcomings. Thus, data is not just an input to an AI cost model, it is the foundation that shapes model behavior and determines the ceiling of its performance.

3.1 Types of Data Used in Engineering Cost Estimation

Engineering cost estimation draws on a rich variety of data sources. Broadly, these can be categorized into structured and unstructured data, each playing a distinct role in model training and prediction:

Structured Data: Structured data refers to information organized in predefined formats (tables, databases) with well-defined fields. In cost estimation, this includes numerical and categorical data such as historical cost records, bills of quantities, project schedules, and engineering parameters. For example, historical cost databases contain past project costs broken down by categories (labor, materials, equipment), often alongside project attributes like scope, size, duration, and complexity. Parametric cost models traditionally rely on such structured datasets by developing statistical relationships between project parameters and costs. A common approach, analogous estimation, directly uses cost data from previous projects as a baseline for new projects of similar nature. Similarly, parametric estimation uses historical project data and attributes (e.g. floor area, component weight, design complexity) to derive cost estimating relationships (CERs) that predict cost from those parameters (Shamim et al., 2025). These structured data sources are typically quantitative and lend themselves well to regression-based ML models and other algorithms that require numerical inputs.

Unstructured Data: Unstructured data is information that does not fit neatly into relational databases or spreadsheets. In engineering projects, a great deal of valuable information is unstructured – for instance, textual descriptions of project requirements, scope documents, technical reports, email communications, and even visual data like blueprints or CAD drawings. AI has opened the door to leveraging unstructured data in cost estimation. Natural Language Processing (NLP) techniques allow ML models to interpret text documents (e.g. project charters, contracts, engineering change logs) to extract factors that could influence cost (Creole Studios Blog, 2023). For example, an AI system might parse through past project documents to identify cost-relevant details such as special design requirements or client-requested features that historically led to cost overruns. This textual information can then be converted into features for a cost model. Likewise, computer vision can be applied to visual data: recent research shows that image recognition on unstructured sources like architectural drawings or BIM models can automatically quantify elements (areas, volumes, counts of components) which feed into cost calculations (Shamim et al., 2025). In effect, AI can transform blueprints and sketches into structured quantities and measurements, improving the accuracy of early estimates. By tapping unstructured data, AI-driven cost estimation goes beyond numbers in a spreadsheet to incorporate knowledge previously locked in documents and images.

Historical and Real-Time Data: The primary data for cost estimation is historical cost data – detailed records of past projects' costs and characteristics. These provide the training examples for supervised learning models, allowing the AI to learn what outcomes (final costs) resulted from certain inputs (project features). In addition, real-time and external data sources are increasingly important. AI systems can integrate data such as current market prices for materials, live labor rates, economic indices, and supply chain information to refine cost predictions (ProjStream, 2024). For instance, if steel or fuel prices spike, an AI model linked to market data can adjust a project's cost forecast accordingly. Project cost is dynamic and influenced by external conditions, so combining historical static data with real-time data streams leads to more robust, up-to-date estimates. Some advanced cost estimation models even ingest data from IoT sensors on job sites or equipment to update costs in real time (Shamim et al., 2025). In summary, the data ecosystem for engineering cost estimation spans structured historical datasets, unstructured textual and visual information, and live data feeds , all of which, when aggregated, provide a rich information base for AI to learn and predict from.

3.2 The Impact of Data Quality, Completeness, and Relevance on Model Performance

The quality, completeness, and relevance of data directly determine the performance of AI/ML models in cost estimation. A model is only as good as the data it learns from – errors or gaps in the data will manifest as errors in the predictions. Several dimensions of data quality are particularly critical:

- Accuracy and Correctness: If the historical cost data contains errors (e.g. misreported expenses, typos, or incorrect project attribute values), the model will learn inaccurate relationships. This can result in systematically biased estimates. For example, if several training examples mistakenly list a major equipment cost as 0 (missing entry) when it was actually significant, a learned model might underestimate costs for projects requiring that equipment. Incomplete or erroneous training data can lead to unreliable models that produce ultimately poor decisions (Mohammed et al., 2025). Just as erroneous inputs yield nonsense outputs, high accuracy in data is a prerequisite for high accuracy in predictions.

- Completeness: Missing data or sparse coverage of certain scenarios can severely hurt model performance. Completeness refers to having all relevant fields filled in and a comprehensive set of examples covering the problem space. If important cost drivers (such as project location or team experience) are not recorded for many projects, the model lacks critical information and may perform poorly or exhibit high uncertainty. In engineering environments, it is common to encounter incomplete data – perhaps some projects lack detailed cost breakdowns or final cost outcomes. Such gaps force the model to either ignore those factors or rely on default assumptions. Research emphasizes that trustworthy AI requires high-quality data along many dimensions including completeness and consistency. When data is incomplete or inconsistent, the model may draw wrong conclusions, leading to flawed cost estimates (Creole Studios Blog, 2023). A practical example is when an estimator's database has plenty of building projects from Region A but almost none from Region B; an ML model trained on it will likely misestimate costs in Region B due to lack of examples (completeness issue in regional coverage).

- Relevance: The data used for training must be relevant to the current prediction task. If there is a mismatch, model performance will degrade. Relevance has a few aspects:

(1) Feature relevance : including input variables that actually influence costs and excluding those that do not. Irrelevant features introduce noise and can confuse the learning process, causing the model to pick up spurious correlations.

(2) Context relevance : using historical data that is applicable to the type of project being estimated.

For instance, training a model mostly on residential building data and then using it to predict costs for a chemical plant will yield poor results; the training data isn't relevant to the new context. Ensuring relevance may involve curating separate datasets or models for different project categories (construction, software, manufacturing, etc.). A relevant dataset covers the range of project types and conditions expected in future estimates. When irrelevant data is included, the model's signals are diluted by noise, harming accuracy. On the other hand, a highly relevant dataset allows the model to focus on genuine cause-effect relations in cost drivers.

Collectively, high data quality (accurate, complete, consistent, relevant data) correlates with superior model performance. Studies show that models trained on clean, comprehensive data significantly outperform those trained on noisy or incomplete data.

Conversely, poor data quality leads to erroneous predictions that can misguide project planning. One industry source notes that inaccurate or incomplete data can lead to flawed cost estimates and undermine the credibility of the estimation process. This underscores the necessity of rigorous data quality management: every percentage of error or omission in the data can propagate through the model into cost estimation errors. Ultimately, investing in good data (through careful collection and validation) pays off in model accuracy. Machine learning cannot magically fix bad data; it will amplify problems if they exist. Thus, ensuring data quality and completeness is one of the most important steps in building reliable cost estimation AI models.

3.3 The importance of Data Preprocessing

Data cleaning and data preprocessing are critical steps in the data science pipeline and are crucial to ensuring data integrity. The need to clean data stems from the presence of inaccuracies, inconsistencies, and missing entries in real data collected by companies and organizations. Data quality directly affects the performance and accuracy of predictive models. Without proper cleaning and preprocessing, models may generate inaccurate or misleading results.

The data cleaning and preprocessing workflow can vary from project to project, but generally includes the following steps: data collection, data cleansing, data integration, data transformation, and dimensionality reduction. Data cleansing involves identifying and correcting errors, removing duplicates, and deleting irrelevant observations.
Another critical aspect is the management of "noisy data"; this type of data are random errors or variations that can result from inaccurate measurements or interference. Some techniques, for example binning, clustering, and the use of machine learning algorithms, are often employed to reduce noise in data. Outlier detection is also an important part of preprocessing, as these outliers can distort the final results.
In addition, inconsistencies in the data, which can derive from errors during collection or input, are typically solved using engineering knowledge tools or by comparing the data with external sources. For example, if the same event is recorded in different ways, such as information about drug administrations in electronic health records, it is essential to standardize this information to ensure that it is correctly represented in the dataset.
Finally, unstructured data, such as text or images, are transformed and organized to facilitate analysis. This process may include encoding categorical variables, normalizing numerical characteristics, and creating new derived variables to make the data suitable for analysis. Dimensionality reduction is another important step, especially when the data contains many variables, to simplify analysis and improve computational efficiency.
In summary, data quality is essential to obtain reliable and accurate models. Investing time in cleaning and preprocessing data can prevent incorrect conclusions and bad decisions, thus improving the reliability of results and the effectiveness of predictive models (Anolytics, 2024).

3.4 Dataset Size, Diversity, and Representativeness

Beyond quality, the size and diversity of the dataset are key factors in developing robust machine learning models for cost estimation. How much data is enough is a common question – and while there is no one-size-fits-all answer, generally more data is beneficial up to a point, provided the data is relevant and representative.

Dataset Size: A larger dataset gives an ML model more examples to learn from, which can improve its ability to generalize. In cost estimation, having thousands of past project examples is ideal compared to just a few dozen. With more data, the model can better capture the variability in project conditions and costs. It reduces overfitting (where a model memorizes the training data but fails on new data) because the model must find patterns that hold across many examples. Additionally, certain modern AI techniques (like deep learning) tend to require big data to reach their full potential. However, the returns on model performance can diminish if additional data is very similar to what's already seen. Quality and relevance still trump sheer quantity. If new data points add new information (e.g. a type of project not seen before, or an extreme scenario), they greatly enhance the model's knowledge base. But if they are near-duplicates of existing records, the benefit is small. Thus, both quality and quantity matter: as one source puts it, the success of AI models depends on the quality and representativeness of the data (quantity), highlighting that volume alone is not enough without representativeness.

Diversity of Data: Diversity refers to having a wide range of examples that cover different aspects of the problem space. For engineering projects, this means data from different project types, different sizes and complexities, different geographic locations, and so on, if the model is meant to be broadly applicable. A diverse dataset ensures that the model does not become overly specialized to one narrow class of projects. For example, if all training data comes from small residential building projects, an AI model might perform poorly on a large commercial project because it never saw something of that scale. Having diverse data helps the model learn the underlying cost-driving principles that transcend individual project idiosyncrasies. It improves the model's robustness and ability to generalize to new cases. Conversely, a lack of diversity can lead to model bias, the systematic error where an AI's predictions are skewed because it has not seen other possibilities. In cost estimation, this could mean consistently underestimating costs for projects unlike those in the training set.

Representativeness: Representativeness is related to diversity but specifically means the dataset's distribution should reflect the true distribution of projects that the model will encounter in practice. A representative training dataset covers all relevant categories and scenarios in proportions similar to reality, ensuring that the model is not biased toward or against any subset. If certain types of projects are underrepresented in data, the model's predictions for those types will be less reliable and potentially erroneous.

From a theoretical perspective, ensuring a large, diverse, and representative dataset helps to minimize both random error (variance) and systematic error in model predictions. A large sample reduces random fluctuations, diverse data prevents overfitting to specific patterns, and representativeness avoids systematic skew. If obtaining more data of certain types is difficult (a common case in engineering, where projects might be few and expensive), techniques like data augmentation or transfer learning can be considered. However, the principle remains: the closer the training data reflects the true universe of future projects, the better the AI model will perform. Practitioners are advised to continuously expand and update their cost databases, as new projects add to the diversity and help keep the model relevant to current trends (for example, incorporating recent data on material price surges or new construction methods) (Mohammed et al., 2025).

3.5 Challenges in Data Collection and Management in Engineering Environments

Gathering and managing the data needed for AI cost estimation is often a major challenge in engineering environments. Unlike internet companies that naturally collect millions of data points, engineering firms (construction companies, manufacturers, etc.) must actively build up their project databases, often from disparate sources. Some key challenges include:

Data Accessibility: Relevant project data is frequently scattered across different departments and systems. Organizations may lack centralized data repositories or standardized processes for collecting project cost data, making it difficult to assemble a complete dataset. For example, the engineering department might have spreadsheets of material costs, the finance office has overall project budgets, and individual project managers keep their own records of change orders. These silos impede the AI model's access to a holistic view of past projects. Data accessibility issues also arise when historical data is archived in non-digital formats (paper documents, legacy databases) that require significant effort to digitize.

Data Quality and Consistency: Even when data is accessible, it may be inconsistent, incomplete, or poorly documented. Missing data fields and inconsistent reporting standards are common. Incomplete or inconsistent data can lead to flawed cost estimates, yet achieving consistency often means overhauling data entry practices and cleaning legacy datasets. This is a substantial challenge in industries where project record keeping has historically been ad hoc. Cost estimators often find that they must spend considerable time cleaning and reconciling data before analysis.

Data Privacy and Security: Engineering projects, especially in domains like defense or infrastructure, can involve sensitive information. Collecting detailed data on costs may raise privacy or confidentiality issues, such as exposing contractor rates, proprietary processes, or personal information (names, salaries). Organizations must adhere to strict data protection regulations and internal policies when handling project data. Ensuring compliance (e.g. anonymizing data, securing databases) adds complexity to the data collection process. Additionally, concerns about data security might make some stakeholders reluctant to share data fully, hampering the completeness of the dataset.

Cost and Effort of Data Collection: Lastly, collecting high-quality data incurs cost and effort that should not be underestimated. It takes time to record detailed cost data during projects, and historically project teams may have focused more on execution than on recording data for future use. There can be cultural resistance to new data entry tasks. Implementing automated data capture systems (such as IoT sensors or integrated software) can help but involves upfront investment. Organizations must recognize data as a strategic asset and invest in data management to reap AI benefits later on.

Overcoming these challenges often requires organizational change: establishing data governance policies, investing in data infrastructure, training staff in data management, and incentivizing complete data collection. Companies that succeed in creating a robust, accessible cost database position themselves to leverage AI/ML tools effectively, while those that do not will find their models constrained by fragmented or low-quality data (Creole Studios, 2023).

Chapter 4

Italdesign Context and AI Implementation in Project Initiation

Italdesign represents one of the most significant companies on the Italian and European automotive scene, combining the stylistic vocation typical of Turin design with an engineering approach oriented towards innovation from the very beginning. The company was officially founded in Turin in 1968 by Giorgetto Giugiaro and Aldo Mantovani, two figures who respectively embodied the creativity of design and technical expertise in the field of automotive engineering (Italdesign, 2023). The company's initial mission was to offer a complete service that integrated body style, technical design and prototype creation, configuring itself as a single interlocutor for car manufacturers looking for original and competitive solutions.

In the first years of activity, Italdesign stood out above all for its ability to combine aesthetics and functionality, quickly becoming a reference partner for large brands such as Volkswagen, Fiat, Alfa Romeo, Maserati and Lotus. They were not just style studies, but real integrated projects which, starting from the sketch, were transformed into working prototypes. This holistic approach has led to the emergence of iconic models that have marked the history of the automobile, including the Volkswagen Golf Mk1 (1974) and the Fiat Panda (1980), both designed under the direction of Giugiaro (Brunelli, 2018). These examples demonstrate how Italdesign has played a decisive role in democratizing automotive design, offering accessible and at the same time innovative solutions. During the '80 and '90 years, the company progressively expanded its expertise, moving from a style focus to a broader vision that embraced vehicular engineering, rapid prototyping and ergonomic study. Technological growth, combined with the ability to anticipate market needs, has allowed Italdesign to present itself as a strategic part-

ner not only for the automotive sector, but also for other industrial sectors. In fact, since the '90 years the company has undertaken projects related to industrial design, rail transport and even the nautical world, consolidating its image as a multidisciplinary creative center (Petrillo, 2015).
A pivotal moment in Italdesign's history was in 2010, when the company became part of the Volkswagen-Audi group. The acquisition by one of the world's largest builders has strengthened its function as an innovative hub, placing it in an international context characterized by significant investments in research and development. Thanks to this integration, Italdesign was able to contribute to the definition of the stylistic and engineering lines of numerous models of the group, while continuing to develop experimental concept cars and advanced mobility projects (Volkswagen Group, 2010).
In recent years, the company has further evolved its mission, positioning itself as a research and innovation laboratory on the mobility of the future. Current areas of activity include not only automotive design, but also the study of solutions related to sustainable mobility, autonomous driving, electrification and urban air mobility systems. Projects such as the Italdesign Pop.Up, developed in collaboration with Airbus and Audi, represent a willingness to explore futuristic scenarios that go beyond the traditional automobile (Italdesign, 2017). In this sense, Italdesign embodies the transformation of a style center into an integrated hub of design, engineering and technological innovation.

4.1 Structure and Organization

Italdesign, in the course of its evolution, has structured its activities through a division into three main departments, which reflect the different skills and areas of intervention of the company: Engineering, Style and Production. This organization allows them to manage the phases from the conception of a new vehicle to its prototype construction in an integrated manner, guaranteeing a synergistic and highly specialized workflow.

The Engineering Department forms the operational heart of the company and it is now the prevailing area of its activities. This is where technical projects are developed and research and development activities are conducted, with the aim of translating style ideas into functional, safe and innovative engineering solutions. Skills range from structural and aerodynamic analysis to mechanical and electronic systems design, through to virtual simulation and physical testing. This department also deals with emerging issues such as electrification, autonomous driving and modular architectures for new generation vehicles.

The Style Department is instead responsible for the creative and aesthetic part, and focuses on defining the exterior and interior design. Its activities include the development of concept cars, the creation of 3D rendering and clay models, and the study of ergonomic and user experience solutions. Traditionally linked to the original identity of Italdesign, this department continues to play a key role in interpreting market trends and defining stylistic languages capable of combining functionality and visual identity.

The Production Department completes the value chain, translating engineering and style designs into physical prototypes and small pre-industrial series. The skills concern the artisanal construction of unique or limited edition vehicles, rapid prototyping, the management of complex production processes and the experimentation of new assembly technologies and materials. This department therefore plays a fundamental role in validating the solutions developed, providing partner car manufacturers with a tangible product on which to conduct tests and evaluations.

The Project Management Engineering Department worked with us to develop the present research thesis within this articulation. In fact, Italdesign, in order to modernize and keep up with technological evolution, requested the support of the Polytechnic University of Turin with the aim of exploring the implementation of Artificial Intelligence in its processes. The interest focuses in particular on the project management team, which represents the central node for the coordination between creativity, engineering and production. The aim of the research is therefore to understand whether and to what extent the adoption of AI tools is actually practicable, and above all to identify in which project management processes these technologies can bring the greatest added value in terms of efficiency, quality and innovation.
The Project Management team of the Engineering Department consists of about thirty professionals, with heterogeneous skills which vary from mechanical and electronic engineering to industrial management and process organization. The multidisciplinarity of the group represents a strong point, as it allows to tackle complex projects from different perspectives, inte-

grating technical, methodological and managerial skills. Within it are senior project managers, responsible for coordinating the most strategic activities and interfacing directly with clients, supported by more junior profiles who take care of the operational progress of orders, the monitoring of deadlines and the collection of project data.

The role of the Project Management team is central to Italdesign, as it has the task of following the projects in all their phases, from start to conclusion. This means ensuring that activities proceed on schedule and at expected cost, while maintaining the expected quality. Project managers act as a bridge between different company functions and external stakeholders, coordinating flows of information, resources and priorities. This mediation work is essential to translate client needs into clear and achievable goals for technical teams. A particularly relevant aspect is relationship management: the team is in fact responsible for maintaining a constant dialogue with all the actors involved, ensuring that they are always updated and aligned on the progress. The ultimate goal is to gain the satisfaction of all stakeholders, ensuring that the client perceives value from the project, that the internal departments operate in a coordinated and efficient manner and that the company strengthens its reputation for reliability and innovation.

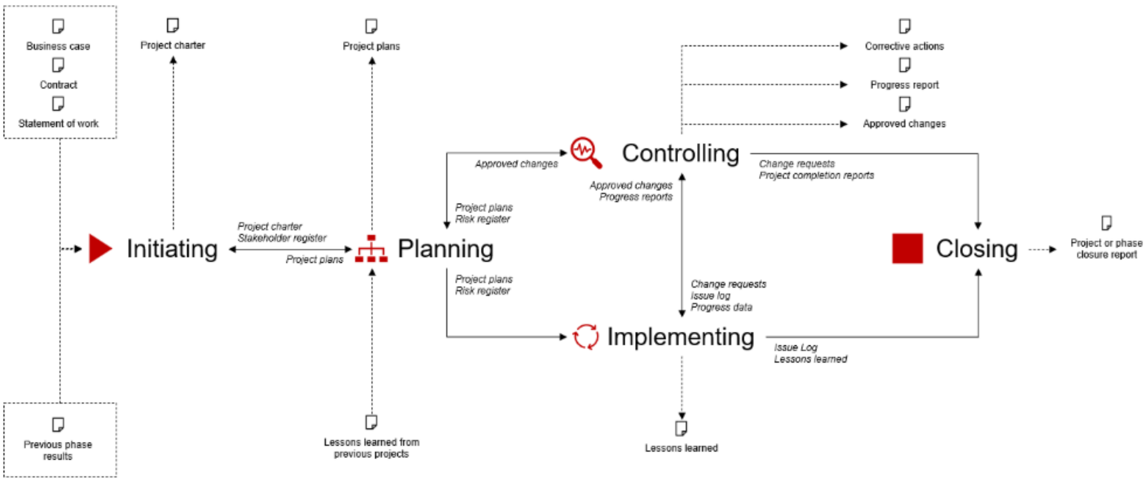

Figure 4.1: A typical project lifecycle.

Although five main phases of the life cycle of a project are traditionally recognised in the project management literature – Initiating, Planning, Controlling, Implementing and Closing – in Italdesign a preliminary phase preceding the actual Initiating takes on particular relevance: the negotiation phase with the client. It represents a strategic moment, since the very possibility of acquiring the order depends on how it is managed.

At this initial stage, that we can call pre-initiation phase, it all starts with the customer sending the company a fundamental document, the Request for Quotation (RFQ), in which are described the desired product and, progressively, the individual components that constitute it are described in more or less detail. It is at this moment that the project manager comes into play and starts the first evaluation and coordination activities. Its task is to draw up a preliminary estimate of the time and cost required to complete the project. To achieve this, the project manager must interface with the different teams belonging to the other company departments, from Style to Production up to the specialist areas of Engineering, collecting all the necessary information to estimate the costs of each component. At the same time, it must make an accurate forecast of the manpower needed, establishing how many people and with which skills will have to be involved in the various phases.
The project manager has a tool at his disposal that supports him in reading and analyzing the RFQs received, named the RFQ Assistant. It is a chatbot developed internally by Italdesign in recent years, trained on a vast dataset of past projects and historical company information. This tool is able to answer even very specific questions about the new RFQs received, providing precise information on the components, estimated times, costs and resources necessary to carry out the project. The RFQ Assistant is designed to understand and interpret technical language and detailed customer requests, thus facilitating the preliminary evaluation process. The integration of this tool results in a considerable improvement in the efficiency of the process, since it allows to obtain quick and accurate answers without the need for manual consultations or intermediate steps. In particular, the ability to obtain precise information on past projects and compare them with new requests significantly reduces customer response time. This tool allows the project manager to focus more on other strategic activities, such as in-depth cost analysis and team planning, thus improving the ability to respond promptly and with greater reliability, reducing potential errors and increasing competitiveness in negotiations with customers.
All of this must be conducted with a strong focus on economic balance: the project manager must guarantee a competitive offer, capable of meeting customer expectations while keeping costs as low as possible. The critical issue of this phase lies indeed in the fact that, in a highly competitive market such as the automotive one, a cost or time margin that is not well calibrated can lead the customer to entrust the project to another company. For this reason, the negotiation and drafting of the first offer represent not only the operational start of the project manager's work, but also a strategic test for the credibility and competitiveness of Italdesign.

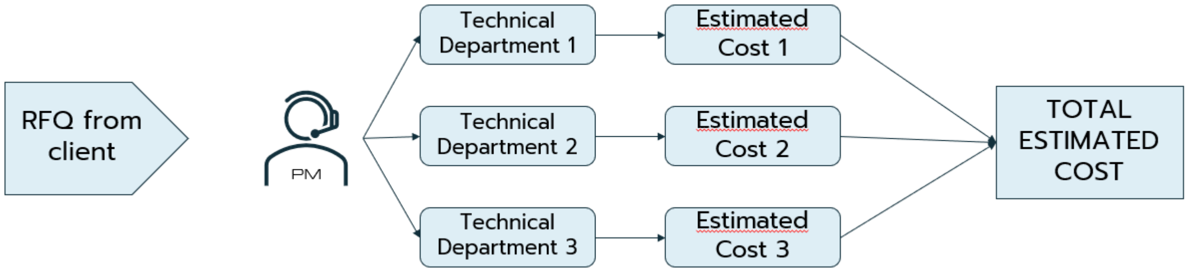

Figure 4.2: Activity before Project Initiation

From a theoretical point of view, Italdesign's approach can be considered an extension of the classical model outlined by the Project Management Institute (PMI), which in its Project Management Body of Knowledge (PMBOK) defines a life cycle divided into five sequential phases. The addition of the pre-initiating phase allows formalizing and enhancing a step that, although not always highlighted in the literature, is crucial in highly competitive industrial contexts: the construction of the relationship with the customer and the definition of the starting contractual conditions. In this sense, Italdesign's model is part of a broader line of studies that underline the importance of the conception and negotiation phase as a distinct moment, in which the project manager's ability to interpret the needs of stakeholders, evaluate technical and economic feasibility and prepare sustainable offers becomes the real discriminant for the success of the project (Kerzner, 2017; Project Management Institute, 2017).

4.2 Introduction of AI in the department

The introduction of Artificial Intelligence (AI) in Italdesign's Engineering Department is a strategic move, aimed at responding to the company's modernization needs and ensuring a competitive positioning in the global market. The reasons behind this choice mainly concern the improvement of operational efficiency, the predictability of results, and the reduction of errors during the execution of projects. As already analyzed previously, the introduction of AI can be beneficial in several areas of project management, in particular for the automation of repetitive tasks, decision support, risk management and predictive analytics, the generation of reports and documentation, as well as in assisting in communicating with stakeholders and suppliers (Mangal, 2023; Project Management Institute Sweden Chapter, 2024).

These tasks, in fact, are those for which AI has already found practical application in numerous business contexts. For example, there are already numerous publicly available AI tools for each of the tasks mentioned above. For repetitive task automation, UiPath is an example of Robotic Process Automation (RPA) that can automate various administrative and operational tasks; for decision support, IBM Watson offers advanced solutions that support information management and predictive analytics; for risk management and predictive analytics, tools like RiskWatch can help identify risks and suggest corrective actions; for report and documentation generation, solutions like Zoho Analytics and Tableau automate reporting and data visualization; finally, for assistance in communicating with stakeholders and vendors, Slack and Microsoft Teams, integrated with AI, enable smoother management of corporate communications.

However, Italdesign, while recognising the effectiveness of these already existing tools, has chosen to focus on a phase of the process which, while crucial, is less explored by the literature and solutions already on the market: the pre-initiation phase. This phase is particularly important in Italdesign, where the initial negotiation process with the client and the definition of the project details are fundamental to the success of the project itself. The pre-initiation phase includes receiving the RFQ (Request for Quotation), estimating costs and times, as well as preliminary resource planning. At this stage, the quality of communication with the customer and the clear definition of expectations are crucial.
After analyzing in detail the process that a project follows in Italdesign, we asked ourselves which part of this process was most appropriate for the integration of an AI tool and, even more important, which part could benefit the most from the implementation of innovative solutions. The objective is to develop a tool that is not only useful to the company, but that responds to specific needs and that is not yet satisfied by solutions already available on the market. Since the focus of the research is to study and analyze the implementation of a new tool, if it is possible and how, we decided to create something useful for the pre-initiation phase, because it is the most undiscovered field.

Which real changes would the implementation of this tool lead to?
First of all, the reading and analysis times of an RFQ are quite long: from the moment the document is received by Italdesign, about a month passes before the customer receives a response. This interval is necessary to allow project managers to develop precise and reliable estimates, contacting the various teams and collecting detailed information on times, costs and resources.

The introduction of an automated tool would make it possible to significantly reduce estimation times, accelerating the initial phase of the project.
Secondly, the use of AI would help improve the accuracy of the estimates in question. Often, in fact, project managers tend to overestimate or underestimate project costs, with the risk that the customer decides to turn to other companies capable of offering the product at a more competitive price. Automating part of the evaluation phase would provide more accurate and reliable estimates, increasing customer satisfaction and reducing the margin for human error.

Chapter 5

Development and Presentation of the AI Tool for Cost Estimation

As already analyzed in 3.5, the project aims to develop an AI support tool for Italdesign project managers, focused on the pre-initiation phase and in particular on the cost estimation of projects. The aim is to speed up and make more precise some activities, such as the analysis of RFQs, without replacing the work of professionals, but providing a reliable tool that complements and improves the existing process. To understand how to make this objective concrete, it is necessary to analyze how the tool was designed and developed. The next phase of the thesis work describes the development process, starting from the analysis of business requirements and available data, up to the functional design of the instrument, the implementation of AI logics and preliminary validation. The criteria used to identify how the tool integrates into the existing flow of project managers will also be illustrated.

The operation of the tool can be described in terms of input, processing and output.

Input: the tool receives an RFQ as input, containing the specifications requested by the customer and, when available, information on the product components. The document is analyzed to extract relevant data, such as type of product, types of customer, type of contract and process.

Processing: using artificial intelligence algorithms, the tool interprets the contents of the RFQ and compares the information with similar projects present in the Italdesign historical database. This phase allows production costs to be estimated by considering time, materials, labor and margins, based on past experiences. Furthermore, AI assigns the project to a cluster of similar projects, facilitating comparative analysis and allowing the rapid identification of similarities with previous projects, useful for refining estimates and identifying any critical issues.

Output: As a result, the tool provides an estimate of project production costs and a classification within a cluster of similar projects. This allows the project manager to have a rapid and coherent preliminary evaluation available, which can subsequently be verified and refined manually, reducing analysis times and increasing the precision of the estimates.

5.1 Phase 1 – Data Analysis and Preparation

The first phase of the project covered data collection and the identification of key parameters affecting the cost of a project. After accessing Italdesign's internal database, with the help of a project manager some usable projects were selected, which include: the RFQ initially sent by the client, the estimated cost and the revenue margin of the company. The RFQ documents were consulted directly in the internal database, while cost information was retrieved from the Appian platform.

In total, at least fifty projects were analysed, mainly related to the group Audi and Volgswagen and other players in the automotive and mobility sector. The RFQ Assistant proved to be very useful, providing precise answers to questions about documents, especially for Audi projects, whose RFQs were in German. Despite this, the answers provided by the chatbot have always been verified manually.

From the analysis of the projects, fifteen main parameters were identified, divided into four macro-groups:
Product: the type of product and components requested by the customer (for example, powertrain, body type).
Customer: the level of customer maturity in the market and the positioning of the brand.
Working Model: the contractual framework with which the project is executed.
Process: the set of activities carried out during the different phases of the project life cycle.

VARIABLE	TYPE
QUICK ESTIMATED COST	Real
YEAR	Int
SELLING MARKET BODY TYPE INTERVENTION POWER TRAIN NATIONAL SAFETY ASSESSMENT PROGRAM JOB SPLIT CUSTOMER MATURITY LEVEL BRAND POSITIONING CONTRACT TYPE IT SYSTEMS PROCESS PHASES PROCESS ACTIVITIES	Bool

Figure 5.1: 15 Parameters

One or more options can be valid for each parameter, with yes/no answers or selections between different possibilities.

5.2 Phase 2 – AI Modeling and Testing

The second phase covers AI modeling and testing of collected data. The main aim is to estimate the cost of a project from the variables identified in the previous phase.

To do this, different Machine Learning algorithms were compared to find the best one capable of understanding the relationship between the characteristics of a project (such as product type, component complexity, customer, contractual methods) and the estimated cost. Each model was tested to understand which was the most accurate and reliable.

To ensure that the results were generalizable and not too tied to the historical data used for training, a technique called Leave-One-Out (LOO) was applied. In practice, the model was trained on data from all but one project (N-1), and then is tested on remaining excluded project. This process is repeated for each project present in the dataset, in order to have a realistic eval-

uation of the model's ability to make predictions even on new projects.
Furthermore, in order to have each algorithm working at its best, an inner Leave One Out Cross Validation method was applied, to choose the best hyperparameters for each model: this method tests different combinations of hyperparameters to select at the end the one that produces the most accurate estimates.To better understand the situation, reference can be made to 5.1.

Outer Iteration	**Outer Test**	**Outer Training**	**Inner Iterations**
1	A	B, C, D	B $\rightarrow$ {C, D}; C $\rightarrow$ {B, D}; D $\rightarrow$ {B, C}
2	B	A, C, D	A $\rightarrow$ {C, D}; C $\rightarrow$ {A, D}; D $\rightarrow$ {A, C}

Table 5.1: Example of nested cross-validation with external and internal iterations

During the test, the model produced several useful pieces of information:

- Predictions for each project: the cost estimate for each RFQ.
- Aggregate assessments: general indicators of accuracy, such as the average error between estimate and real cost.
- About the parameters you choose: Which model configurations worked better and how often.
- Residue analysis: verifies that the differences between estimates and real values do not present systematic errors or unwanted patterns.

The metrics used to compare model performance are:

- MAE (Mean Absolute Error): average absolute error between estimate and real value.
- RMSE (Root Mean Squared Error): square root of the average of the squares of the errors, useful for penalizing large errors.

- MAPE (Mean Absolute Percentage Error): average percentage error, useful for comparisons between projects of different sizes.
- R^2 (R-Squared): measures how much the model can explain the change in data.
- Statistical diagnostics: Shapiro test (verification of normality), Durbin-Watson (autocorrelation), statsmodels and ACF tools.
- Utility: Counter to count the combinations of tested parameters, datetime to identify each individual execution.

Next, the data is loaded from an Excel file and cleaned to ensure a neat dataset:

- Deleting unnecessary columns (Offer Number and Actual Cost).
- Light data cleaning: Removing extra spaces in strings, converting yes/no values to 1/0, and removing rows with missing data.

For the modeling part , the variable to be predicted is Estimated Cost (y), while the other variables are used as features X, excluding some irrelevant columns such as Name, Margin, and Offer Value. The main function of the script, called run(...), handles the entire experiment and assigns each pattern a unique identifier (model id).

Nested LOO validation is applied:

- Outer LOO: evaluates how much the model can generalize, testing each project individually with the others as training.
- Inner LOO: Performs Grid Search within the external training set, selecting parameters that minimize the mean absolute error.

During each external cycle, the model is trained, the best parameters are recorded, and out-of-sample predictions, that is, estimates on projects not used for training, are generated. Finally, the hyperparameters and residues of the model are analyzed, to verify that there are no systematic errors or unwanted patterns (such as lack of normality or autocorrelation).

Models tested include:

- OLS (Linear Regression): simple linear model that tries to find a straight line that best approximates the data.
- Ridge: Similar to OLS, but adds a penalty to reduce the risk of errors when variables are many or related to each other.
- k-NN (k-Nearest Neighbors): Estimates the cost of a project by comparing it with more similar projects in the dataset.
- Decision Tree: Tree structure that divides projects based on key characteristics, producing step by step estimates.
- Gradient Boosting: combines multiple decision trees in series, improving estimates step by step by correcting previous errors.
- Random Forest: combines many decision trees in parallel to obtain more stable estimates that are less influenced by isolated errors.
- Extra Trees: Random Forest variant that introduces more randomness, improving the robustness of the model.
- AdaBoost: method that combines simple models (weak learners) in sequence, giving more weight to projects that had been poorly estimated previously.
- MLPRegressor (Multilayer Perceptron): neural network that simulates a small artificial brain, capable of recognizing complex patterns in data.

5.3 Phase 3 – Optimization and Validation

The third phase of the project was dedicated to tool optimization and validation. The primary objective was to identify the most effective model for estimating project costs while ensuring that the obtained results were both accurate and reliable. To achieve this, several performance metrics were employed, each providing a different perspective on model quality.

Mean Absolute Error (MAE): measures the average absolute deviation of predictions from the actual values. Ideally, this indicator should approach zero, as it quantifies the typical error in the same units as the target variable. MAE is particularly useful when projects are relatively homogeneous in scale, as it provides an intuitive sense of the expected magnitude of error. Root Mean Squared Error (RMSE): similar to MAE, but by squaring residuals before averaging and then taking the square root, it penalizes large errors more heavily. This makes RMSE especially relevant in cost estimation, where occasional large deviations can be very problematic from a managerial perspective.

Mean Absolute Percentage Error (MAPE): expresses errors as a percentage of actual values, allowing comparisons across projects of different scales. While valuable for heterogeneous datasets, MAPE is sensitive to very small actual values: even a minor absolute error can translate into an extremely large percentage deviation. Moreover, its interpretation must consider context: for example, a 10% error in a €100 project amounts to only €10, whereas the same percentage error in a €10 million project corresponds to €1 million.
In tables, the scale is from 0 to 1, with 1 representing 100% percent error. If the value exceeds 1, it means that it exceeds 100% percentage error.

Coefficient of Determination (R^2): evaluates the proportion of variance in the target variable explained by the model. An R^2 of 1 indicates perfect prediction, whereas an R^2 of 0 means the model performs no better than the mean. Negative values, in turn, signal that the model is less accurate than simply using the average cost as a predictor. In practice, R^2 is informative for assessing whether the model successfully captures the overall direction and variability of costs, rather than only the absolute magnitude of errors.

The choice of evaluation metric ultimately depends on the managerial priorities of the analysis. When the goal is to minimize large financial deviations, avoiding substantial monetary errors in euros, MAE and RMSE should be prioritized. Conversely, when relative accuracy across projects of different sizes is more relevant, MAPE becomes the most suitable measure, despite its limitations for very small values. A balanced interpretation of these indicators was therefore necessary to ensure that the selected model not only achieved statistical accuracy but also delivered practical reliability in project cost estimation.

To represent monetary values we used a fictitious currency, which we called ItalDesign (ID) coin, in order not to reveal sensitive data that would affect the company's privacy.

Experiment n.1

The first experiment was conducted on a dataset of 35 projects, with an average estimated cost of approximately 2,266 million of ID coins. The performance of the models varied significantly depending on both the algorithm and the distribution of project costs. A key characteristic of this dataset is the strong concentration of projects below 1,65 million of ID coins, which introduces an imbalance: models tend to perform reasonably well within this lower cost range, but predictions for larger projects are much less accurate. This pattern directly affects the evaluation metrics.

Model	MAE	RMSE	MAPE	R^2
MLP_154520	2 244 089.28	6 152 854.13	1.06	-0.15
DT_153257	2 163 226.24	5 390 296.66	5.17	0.12
ETs_154131	2 026 572.89	4 969 197.83	5.33	0.25
GB_153314	2 214 728.73	6 056 385.04	7.46	-0.12
AdaBoost_154504	2 811 855.96	6 591 923.23	13.29	-0.32
k-NN_153244	2 595 864.87	5 984 248.40	14.04	-0.09
RF_153828	2 296 533.68	5 013 607.45	16.02	0.23
Ridge_153238	3 720 196.73	5 999 678.49	55.26	-0.10
OLS_153224	4 066 289.25	5 743 332.22	57.94	-0.00

Table 5.2: Comparative results of regression models, experiment 1

The Extra Trees (ETs) and Decision Tree (DT) models achieved the lowest absolute errors (MAE around 2,055–2,145 million of ID coins) and percentage error(517%-533%) and positive though modest R^2 values (0.12–0.25). Their tree-based structure enables them to capture non-linear thresholds and rules in the lower-cost projects, where the majority of the data lies. However, they generalize poorly for projects exceeding 1,65 million of ID coins, which explains why their RMSE remains high and their predictive power limited.

The Random Forest (RF) also reached comparable results ($R^2 = 0.23$), but with a higher MAE, indicating that while the ensemble reduces variance, it does not necessarily improve accuracy for the underrepresented high-cost projects. Similarly, Gradient Boosting (GB) produced mixed outcomes: despite being designed to refine residual errors iteratively, it underperformed here (negative R^2), likely because the small number of large projects introduced instability during

training.
On the other hand, linear models (OLS, Ridge) performed poorly across all metrics, with extremely high MAPE values (550–580%). This confirms that linear assumptions are insufficient to model the heterogeneity of project costs, particularly when the dataset contains both small and very large values.
Interestingly, the Neural Network (MLP) delivered results comparable to the best tree-based models in terms of MAE, but at the cost of a very high RMSE and a negative R^2. This suggests that while the network can approximate average-level predictions, it struggles to adapt to the skewed distribution of costs and suffers from overfitting given the limited sample size.

Experiment n.2

In this revised experiment, projects exceeding 1,65 million of ID coins were excluded, leaving a dataset of 29 projects with an average estimated cost of approximately €283,800 ID coins. The rationale was to assess whether restricting the sample to a more homogeneous cost range would improve model performance.

Model	MAE (€)	RMSE (€)	MAPE	R^2
MLP_160311	262 509.14	456 078.89	1.08	-0.46
DT_155617	230 145.25	376 778.14	1.25	0.00
GB_155629	238 622.50	418 284.02	5.16	-0.23
RF_155928	223 587.58	317 799.23	5.60	0.29
AdaBoost	249 380.11	366 977.74	6.04	0.06
k-NN_155607	246 024.36	366 571.71	7.28	0.06
ETs_160105	317 949.45	489 098.94	7.79	-0.68
Ridge_155603	276 198.17	411 633.40	8.77	-0.19
OLS_155556	695 614.08	830 710.85	20.63	-3.84

Table 5.3: Comparative results of regression models, experiment 2

The results show a general improvement in error stability compared to the full dataset, but several limitations remain. Models such as Random Forest (RF) and Decision Tree (DT) achieved the best balance between MAE and RMSE, with RF in particular reaching the highest R^2 (0.29). This indicates that ensemble tree-based methods are more capable of capturing the variance in this restricted dataset, although the predictive power remains modest.

Interestingly, Neural Networks (MLP) reported a relatively low MAE but a negative R^2 (-0.46), showing that while predictions are numerically close to actual values on average, the model fails to explain variance in project costs. Similarly, Gradient Boosting (GB) and Extra Trees (ETs) underperformed, likely because the reduction in data size limited their ability to build strong ensembles.
Moreover, the R^2 values are very low across all models, even for those with acceptable MAE. This highlights that while models can approximate central tendencies, they are not capturing the underlying variability of costs. The relationship between MAPE and R^2 supports this interpretation: models with lower percentage errors do not necessarily achieve higher explanatory power, reinforcing the idea that minimizing absolute error does not equate to explaining variance.

In summary, restricting the dataset to projects under €1,65 million of ID coins improved numerical accuracy (especially in MAE and RMSE) but did not solve the core issue of weak explanatory performance. The models remain biased toward underrepresenting variability, and their predictive reliability is therefore limited. This suggests that additional features or a more balanced dataset across cost ranges would be necessary to achieve robust cost estimation.

Experiment n.3

The third experiment expanded the dataset to 48 projects, thereby increasing heterogeneity in project costs. The results highlight both improvements and new challenges introduced by the broader cost distribution.

The best-performing models in terms of explanatory power are Random Forest (RF) (R^2 = 0.39) and AdaBoost (R^2 = 0.28), followed by Ridge Regression (R^2 = 0.32). RF achieves the lowest MAE (3,988 M DT coins) and RMSE (6,749M DT coins), suggesting that its ensemble mechanism is particularly effective in handling the variability introduced by additional projects. By averaging multiple decision trees, RF reduces variance and adapts to non-linear structures better than single-tree methods such as DT.
AdaBoost also shows competitive performance, with moderate errors and the second-best R^2. Its sequential boosting framework enables it to capture complex patterns, although it remains sensitive to noise, which partly explains the higher MAE compared to RF.

Model	MAE (€)	RMSE (€)	MAPE	R^2
MLP_164103	4 710 701.01	9 831 513.86	1.54	-0.30
k-NN_161307	4 235 106.13	8 028 467.40	12.35	0.14
ETs_163233	4 516 810.28	8 315 667.66	19.00	0.07
DT_161419	4 058 846.72	8 109 440.96	19.38	0.12
AdaBoost	4 297 174.72	7 351 698.11	28.69	0.28
RF_162619	3 987 739.39	6 745 031.19	32.65	0.39
GB_161456	4 729 456.36	7 749 516.82	50.93	0.20
Ridge_161259	4 935 873.00	7 120 172.20	71.05	0.32
OLS_161249	35 114 286.67	187 417 178.20	108.83	-469.72

Table 5.4: Comparative results of regression models, experiment 3

Surprisingly, Ridge Regression ranks among the top models by R^2, despite its linear assumptions. This suggests that with the larger dataset, linear trends become more detectable, and regularization helps avoid extreme coefficient estimates. However, its MAE and RMSE remain higher than those of RF, indicating weaker absolute precision.

By contrast, Neural Networks (MLP) underperform substantially, with a very high MAE (4,708M ID coins) and a negative R^2, confirming difficulties in generalization when faced with a heterogeneous dataset. Similarly, OLS collapses completely, producing astronomical errors (MAE > 34,65M ID coins, $R^2 = -469$), highlighting its inability to cope with cost variability and outliers.

Another important insight is the deterioration of MAPE across most models. RF and AdaBoost, despite achieving the best R^2 values, record high percentage errors (327% and 286%). This reflects the dominance of high-value projects in the expanded dataset: as costs increase, even moderate absolute deviations translate into very large relative errors.

In summary, the inclusion of 13 additional projects amplified dataset heterogeneity, favoring ensemble methods (RF, AdaBoost) that balance bias and variance. Linear regression improved in explanatory terms but remains less precise. Conversely, models highly sensitive to distributional shifts (MLP, OLS) performed poorly. The results underscore how dataset size and variability directly affect both model ranking and the trade-off between absolute (MAE/RMSE) and relative (MAPE) accuracy.

Experiment n.4

In the fourth experiment, the same 48 projects were restructured through a manual clustering procedure aimed at grouping projects into more comparable categories. Although the clusters remained relatively large and not highly precise, the reorganization significantly influenced the performance of the models.

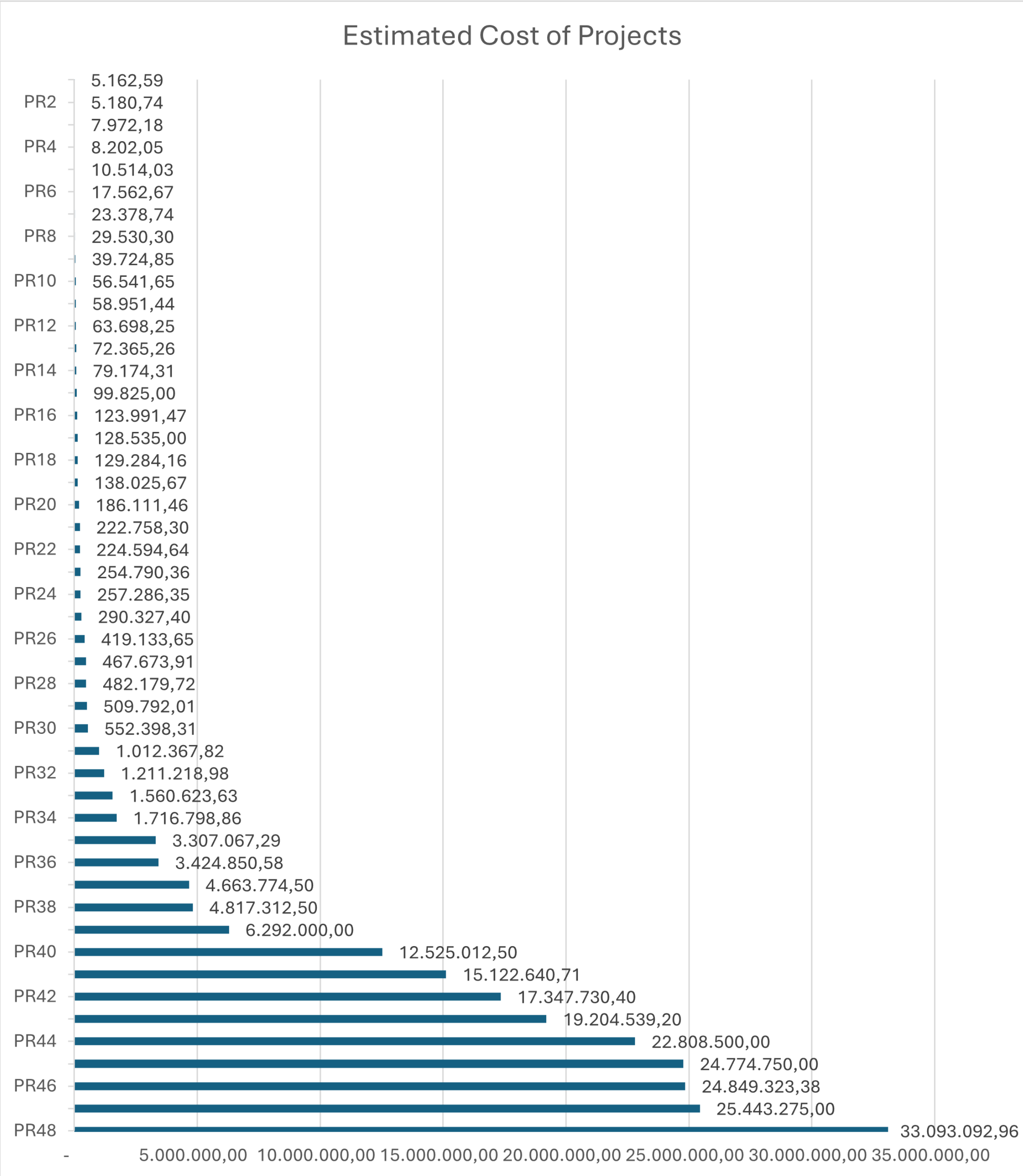

Figure 5.2: Estimated Cost of Projects.

Model	MAE (€)	RMSE (€)	MAPE	R^2
MLP_093636	4 705 441.81	9 826 602.82	1.72	-0.29
k-NN_091025	4 002 509.42	7 710 368.64	11.69	0.20
ETs_092847	3 348 852.71	6 893 629.44	12.91	0.36
AdaBoost	3 544 036.53	6 409 610.37	18.24	0.45
DT_091219	4 046 052.23	8 649 155.94	20.38	-0.00
RF_092309	3 774 858.14	6 266 838.93	22.61	0.47
GB_091253	3 869 944.77	6 412 303.73	24.62	0.45
Ridge_091004	4 635 499.39	6 076 206.09	61.10	0.51
OLS_090949	4 337 196.25	5 610 083.33	68.39	0.58

Table 5.5: Comparative results of regression models, experiment 4

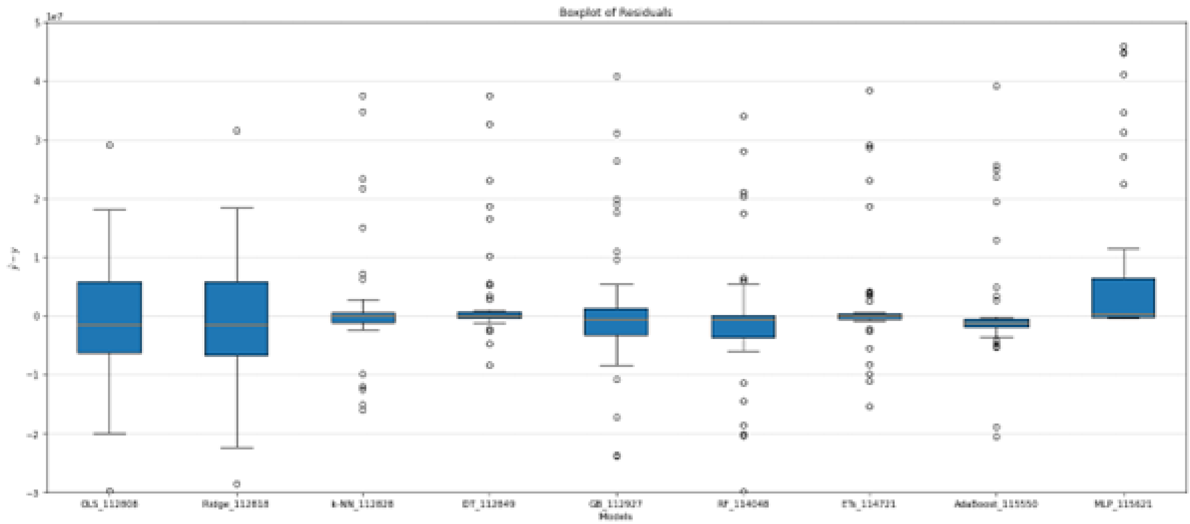

Figure 5.3: Boxplot of residuals - experiment n.4

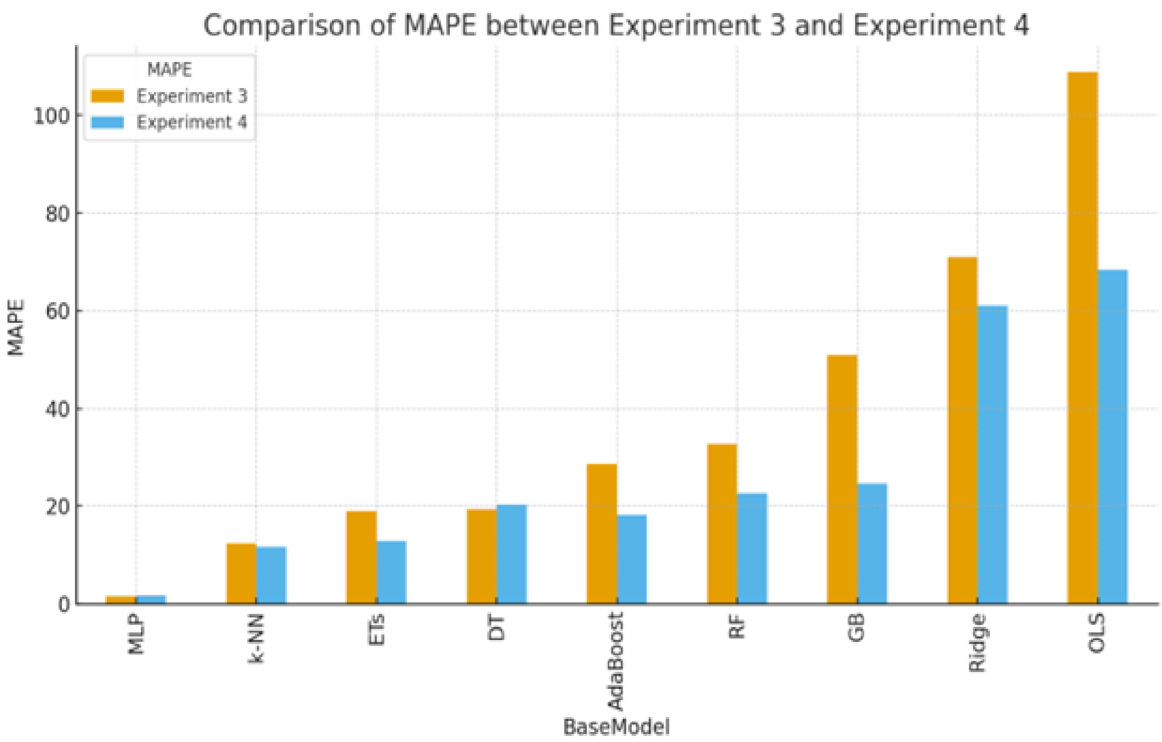

Figure 5.4: MAPE comparison between experiment 3 and 4

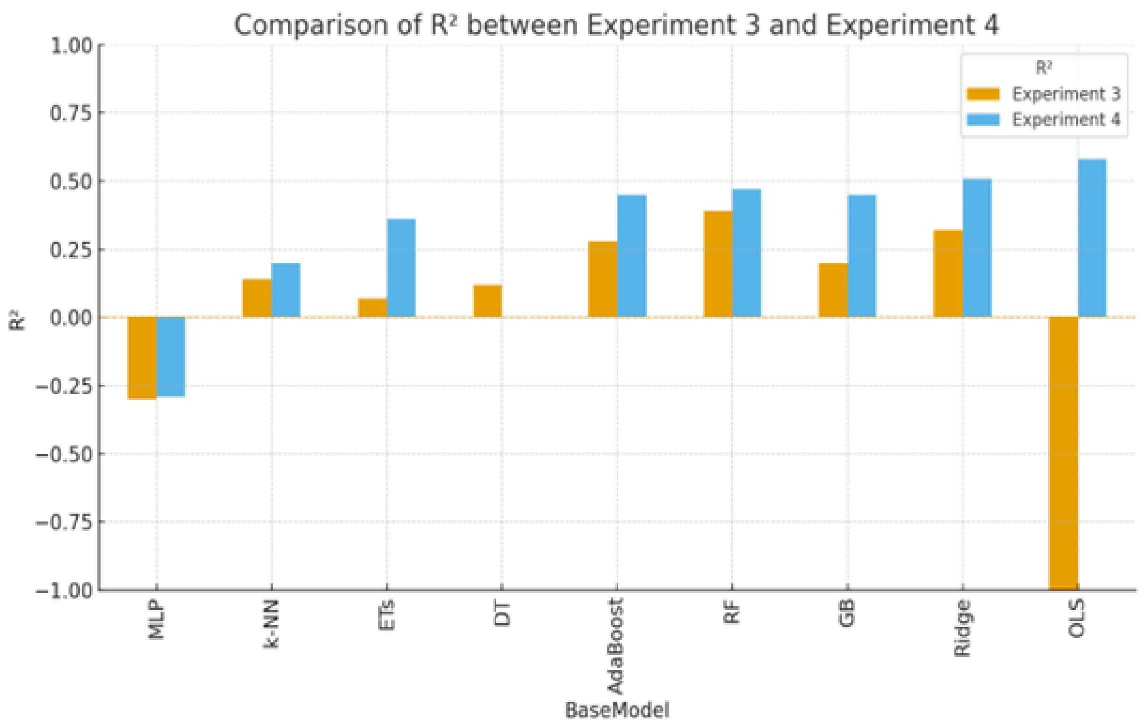

Figure 5.5: R^2 comparison between experiment 3 and 4

The introduction of an internal clustering approach (0–55k ID coins; 55k–550k ID coins;

>550k ID coins) led to a substantial improvement in the performance of the models, particularly in terms of MAPE and R^2.

Looking at the two sets of results, clear differences emerge. In Table 1, many models exhibit very high MAPE values (for instance, Ridge (711%) and OLS (1083%)) indicating extremely large percentage errors that undermine their reliability. Only the MLP reports a lower MAPE (154%) and the corresponding R^2 is negative (-0.30), meaning the model fails to explain the variance in project costs. More generally, R^2 values in Table 1 are consistently low or even negative, highlighting that most models are unable to capture the underlying data structure.

By contrast, Table 2 shows a marked improvement. MAPE values decrease significantly across several models: for example, Ridge drops from 711% to 611%, Random Forest from 327% to 226%, AdaBoost from 289% to 182%, and OLS improves drastically from 108.83 to 68.39. More importantly, R^2 values increase considerably: OLS rises from -469.72 to 0.58, Ridge from 0.32 to 0.51, Random Forest from 0.39 to 0.47, and AdaBoost from 0.28 to 0.45. This indicates that the models in Table 2 explain the variance of the data much more effectively, delivering more stable and coherent results.

Overall, the second configuration (Table 2) produces more accurate and interpretable models, primarily due to a better balance between reduced MAPE and positive R^2. Clustering helped reduce heterogeneity and improved the alignment between model assumptions and data structure. These results confirm that even a coarse clustering strategy can significantly enhance predictive reliability. By reducing within-cluster variability, the models gain the ability to explain trends more effectively, resulting in improvements in both absolute accuracy (MAE, RMSE) and relative accuracy (MAPE, R^2).

Experiment n.5

One of the main challenges in project cost estimation lies in the extreme variability of project costs within the dataset. In previous experiments, the models produced very high absolute errors even for projects with actual values as low as 5,500 ID coins. This made the evaluation results difficult to interpret, since a large average error does not necessarily reflect poor performance across all projects, but rather the disproportionate influence of a few very large cases.

To address this issue, the dataset was reorganized into three distinct groups based on cost ranges, creating a form of manual clustering. The rationale behind this approach was to reduce heterogeneity within each group, thereby allowing the models to be evaluated on more comparable subsets of projects.

The three groups were defined as follows:

- Group 1 (0 – 550k): small projects with relatively limited budgets, where precision in absolute terms is critical.
- Group 2 (550k – 6,6M): medium-scale projects, where variability increases but still falls within a manageable range for predictive models.
- Group 3 (6,6M – 34,1M): large-scale projects with very high costs, where relative accuracy (MAPE) is more important than absolute deviations, given the financial scale involved.

This segmentation enables a more balanced evaluation of model performance, making it possible to assess whether algorithms are more effective at estimating small, medium, or large projects, rather than averaging errors across an excessively heterogeneous dataset. Moreover, it provides clearer insights into the strengths and limitations of each modeling approach, supporting the identification of algorithms best suited for different project cost ranges.

Group 1

AVG Estimated Cost = 152.147,18 ID coins

Model	**MAE**	**RMSE**	**MAPE**	**R^2**
ETs_140629	86 293.19	136 287.29	0.77	0.19
DT_140151	86 031.21	139 302.75	0.80	0.16
GB_140202	95 444.33	134 791.66	1.91	0.21
RF_140457	98 279.14	130 290.72	3.03	0.26
MLP_140823	116 897.67	159 469.62	3.38	-0.10
OLS_140115	109 261.24	130 100.18	3.72	0.27
Ridge_140122	104 951.18	131 878.96	3.89	0.25
k-NN_140125	112 953.51	149 019.38	3.99	0.02
AdaBoost_140813	121 312.53	173 125.20	5.23	-0.30

Table 5.6: Comparative results of regression models (fifth dataset, group 1)

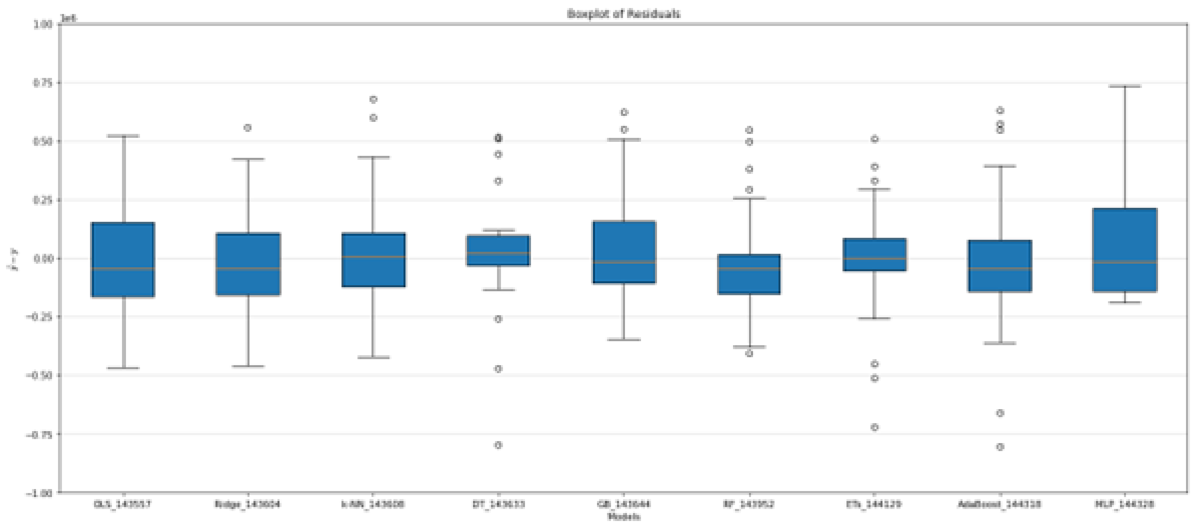

Figure 5.6: Boxplot of residuals group 1.

ETs : best MAPE, still 6 outliers

DT : has the most compact boxplot of residuals but 7 outliers

Group 2

AVG Estimated Cost = 2.855.840 ID coins

Model	**MAE**	**RMSE**	**MAPE**	**R^2**
k-NN_142532	1 819 528.56	2 126 654.45	1.02	-0.34
MLP_142608	2 049 000.19	2 559 385.44	1.06	-0.94
GB_142537	1 994 738.36	2 358 169.06	1.11	-0.64
OLS_142525	2 144 952.01	2 743 956.41	1.15	-1.22
RF_142549	1 863 539.52	2 109 662.57	1.19	-0.32
AdaBoost_142606	1 889 789.49	2 297 600.16	1.23	-0.56
ETs_142558	2 235 118.54	2 500 746.45	1.39	-0.85
DT_142535	2 380 225.16	2 621 878.26	1.41	-1.03
Ridge_142531	21 883 167.94	64 340 729.74	4.31	-1222.52

Table 5.7: Comparative results of regression models (fifth dataset, group 2)

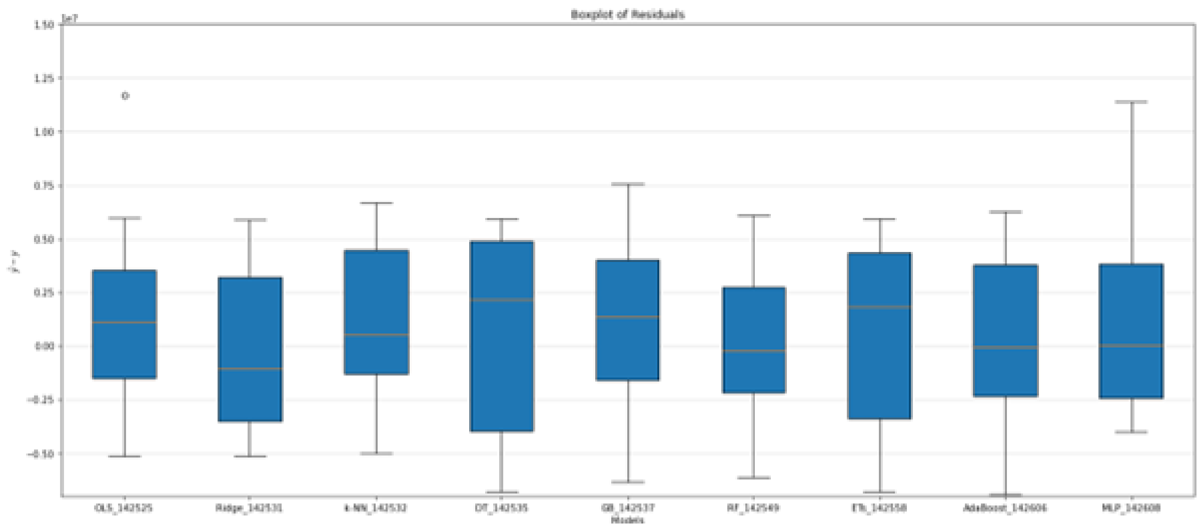

Figure 5.7: Boxplot of residuals.

Group 3

AVG Estimated Cost = 21,685,429 ID coin

Model	**MAE**	**RMSE**	**MAPE**	$\mathbf{R^2}$
GB_093435	4 401 323.32	5 816 609.48	0.27	-0.14
Ridge_093429	5 804 002.57	7 315 644.47	0.30	-0.52
RF_093444	6 002 466.81	7 474 025.75	0.31	-0.43
k-NN_093429	5 815 769.81	7 189 704.71	0.34	-0.52
OLS_093422	6 375 586.70	7 311 947.62	0.37	-1.10
ETs_093452	7 031 832.71	7 718 988.78	0.38	-0.95
AdaBoost_093500	7 315 198.50	8 592 253.75	0.39	-0.81
DT_093433	7 013 707.04	8 488 268.87	0.44	-1.88
MLP_093502	13 857 351.02	15 084 939.86	0.67	-6.38

Table 5.8: Comparative results of regression models (fifth dataset, group 3)

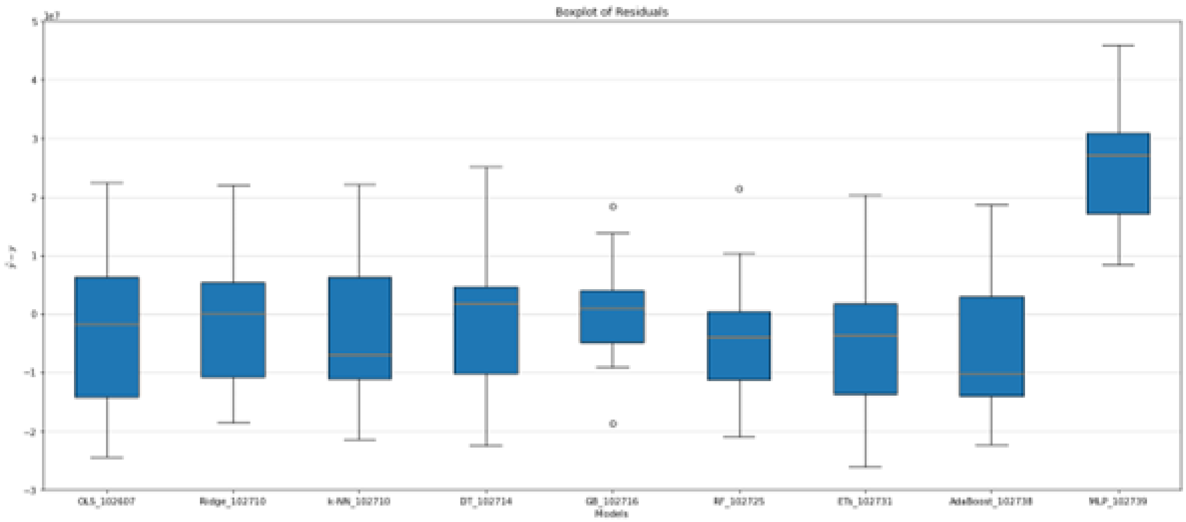

Figure 5.8: Boxplot of residuals.

Output analysis

The results reveal an important relationship between dataset size, cost variability, and the type of algorithm that performs best.

In the first group, tree-based methods such as Decision Trees and Extra Trees emerge as the most effective. This outcome can be explained by the relatively moderate number of observations combined with a limited cost range. Tree-based algorithms are particularly well-suited to capturing non-linear patterns and threshold effects, which are often present in cost estimation problems. The ensemble variant (ETs) mitigates the variance of a single decision tree, producing more stable predictions while preserving interpretability.

In the second group, the dataset is extremely small, making complex models prone to overfitting. Here, k-Nearest Neighbors (k-NN) and Random Forests deliver the best performance. The success of k-NN lies in its local learning approach: new projects are predicted based on their similarity to past cases, a method that is effective when the sample is scarce but representative. Random Forests, on the other hand, reduce the instability of single decision trees by averaging across many of them, which provides robustness even with a small dataset.

Finally, in the third group, the cost variability is very high despite the small number of cases. In this setting, Gradient Boosting clearly outperforms the other algorithms. Its sequential learning mechanism, where each tree corrects the residuals of the previous one, makes it capable of modeling complex and heterogeneous cost structures. This explains the relatively low mean

Group (Cost Range)	Data Size	Best Algorithms	Strengths	Limitations
Group 1 (0–550k)	29 projects	Extra Trees (ETs), Decision Tree (DT)	Capture non-linear patterns in small to medium datasets; effective with limited cost variability; easy interpretability.	Sensitive to small changes in data; single trees may overfit, but ETs mitigate variance.
Group 2 (550k–6,6M)	10 projects	k-Nearest Neighbors (k-NN), Random Forest (RF)	Robust with very small samples; k-NN leverages similarity between projects; RF stabilizes predictions by averaging multiple trees.	k-NN depends strongly on the choice of distance metric; RF still limited when data is extremely scarce.
Group 3 (6,6–34,1M)	9 projects	Gradient Boosting (GB)	Sequentially corrects errors, capturing complex, non-linear relations; adapts well to wide cost variability; achieves low relative error (MAPE).	Risk of overfitting with very small datasets if not tuned; less interpretable than simpler models.

Table 5.9: Best-performing algorithms by project cost range, with strengths and limitations

absolute percentage error (MAPE), showing that Gradient Boosting adapts better to projects with large financial scales and diverse patterns.

In general, linear models perform worse because they fail to capture non-linear patterns. A central question is why the best-performing algorithm changes when different datasets, each one with a different size (e.g., the first group with 29 projects vs. the second group with 10) are loaded. With very small datasets, each observation carries enormous weight and can randomly change the output. A simple model such as OLS or Ridge may appear weak with 29 data points but competitive with only 10, because under such conditions complexity does not pay off. Conversely, more flexible models (RF, GB, MLP) tend to overfit easily on reduced samples, which explains the variation in ranking. Put differently, with few data points the bias–variance trade-off favors simpler models, whereas with larger samples, more complex models such as Gradient Boosting, Random Forests, or Neural Networks have enough observations to learn non-linear structures effectively and thus achieve superior performance.
Overall, these findings highlight that there is no universally best algorithm: the performance depends heavily on both the scale of the costs and the amount of available data. The only pattern found was with the ensemble methods which are the best performing; probably, thanks to their complex structure, they are able to notice smaller or hidden patterns.

5.4 Analysis and future work

The performance analysis of machine learning algorithms is closely linked to the quality and quantity of data available. The choice of model, dataset management and pre-processing techniques represent determining factors for obtaining reliable and generalizable results. In this context, it is essential to understand how the complexity of the model interacts with the size of the dataset, what the critical issues arise from reduced or unbalanced data are and what strategies can be adopted to improve overall performance. Moreover, when resorting to clustering techniques, the selection of the most appropriate approach depends on the availability of key information, such as cost, and the intrinsic nature of the data. The following paragraphs elaborate on these aspects and outline the next steps to optimize the modeling process.

Output of the research

After a deep analysis of the output obtained during the different experiments, we can summarize the content in three fundamental points:

1. Complex models, such as ensemble methods (e.g. Random Forest, Gradient Boosting), tend to provide superior performance when you have large, diverse datasets. These models are able to capture nonlinear relationships and complex interactions between variables, improving predictive ability. However, in the presence of small datasets, even simpler models, such as Decision Tree or Ridge Regression, can be effective, especially if appropriately optimized and regularized. The choice of model must therefore be guided not only by the complexity of the problem, but also by the availability and quality of the data.

2. Very small or highly unbalanced datasets represent a significant critical issue for the performance of machine learning algorithms. In these scenarios, the risk of overfitting increases, resulting in a reduction in the generalization capacity of the model. Furthermore, the presence of poorly represented classes can lead to bias in predictions. To mitigate these problems, techniques such as data augmentation, resampling (for example SMOTE for class balancing) or integration of data from external sources can be used.

3. Currently, clustering is cost-based as the primary metric. However, when the cost is not known, alternative approaches can be taken, including:

    - Similarity-based clustering: Using metrics such as Euclidean distance, cosine, or correlation to group similar elements.
    - Hierarchical clustering: useful for exploring relationships between groups without defining the number of clusters a priori.
    - Density-based clustering (DBSCAN): identifies clusters based on point density, ideal for data with nonlinear shapes.
    - Model-based clustering (e.g. Gaussian Mixture Models): assumes that the data come from probabilistic distributions, providing a more robust estimate in uncertain contexts.

    These approaches allow coherent groups to be created even in the absence of economic information, based on intrinsic characteristics of the data.

Next steps:

1. Continue testing: Test different algorithms to identify the best trade-off between accuracy, interpretability and computational complexity.
2. Expand the dataset: The goal is to achieve a large, clean and balanced dataset, reducing the risk of bias and improving the robustness of models.
3. Eliminate the need for clustering: achieve a dataset size that allows direct training of predictive models without having to resort to preliminary clustering techniques.

Gains of the research and benefits for the company

1. Feasibility Study: The thesis provided a clear feasibility study, offering the company an assessment of the opportunities and practical conditions for adopting AI-based solutions. The results obtained are encouraging: some algorithms have been identified capable of correctly analyzing the input data and the performance of the developed tool is in line with initial expectations. However, there is still a lack of comparative validation of the instrument's performance compared to an analysis conducted by human experts, which is fundamental to confirm the effectiveness of the system in real contexts.
2. Analysis of Organizational Data: The analysis of internal data highlighted that the current database could benefit from increased structuring. At the moment, documents and project information are available but distributed in folders with non-uniform structures, while economic and technical data are stored on different platforms. Creating a centralized database that consistently integrates both technical and economic information would quickly provide sufficient data volume to train AI models effectively. This integration represents a strategic step to improve data quality and accelerate analysis processes.
3. An Operational Starting Point: The result of the work was not purely theoretical: the thesis produced a working prototype, which is a concrete basis on which the company can build, refine and scale its solutions. This tool represents an operational starting point, transforming research into tangible results and paving the way for future developments oriented towards the implementation of large-scale AI systems.

Future evolution of the tool

Currently, the tool described in the document is a working prototype developed in Python, conceived as part of a preliminary study to validate the approach and demonstrate its technical feasibility. Although it already executes the main logic envisaged, it is not yet ready for operational use: to make it effectively usable by Project Managers, hardening and scalability activities are needed, starting from an expanded database (greater data coverage and quality, update procedures, control versions) and the construction of a dedicated user interface that makes the functions accessible even to non-technical personnel. This direction also includes integration with company systems (authentication, permits), monitoring and logging, automated tests and usage documentation. In summary, the current prototype constitutes a solid foundation on which to build a mature platform, capable of generating concrete value for Project Managers.

In the image shown in 5.9 there is a representation of how the tool should ideally work in a future implementation. The flow starts from a database, in which the data initially collected (excel files for example) are made available to the AI Tool, which processes the information and produces the calculation results. The processing flows into a User Interface (UI), designed to make interaction with the tool simple and intuitive. Through this interface, the Project Manager (PM) enters the project variables deriving from the Request for Quotation (RFQ), which represent the necessary input parameters. Finally, the system provides an output estimate of the costs associated with the project, thus allowing it to support decisions in the planning and budgeting phase.

To achieve this mature version of the tool, some basic steps are needed:

- Creation of a structured database, capable of managing data proving from different sources in a scalable and coherent manner.
- Further explore the selection of the most suitable AI model to apply, evaluating which machine learning approach guarantees the best performance in terms of accuracy and generalization.
- Review the new process by evaluating both the current ("as is") and future ("to be") workflows, to understand the impact of the operational and organizational methods in use in the way the tool is introduced.

- Develop a new intuitive interface that allows project managers to easily send requests, making the adoption of the tool immediate and natural even for non-technical users.

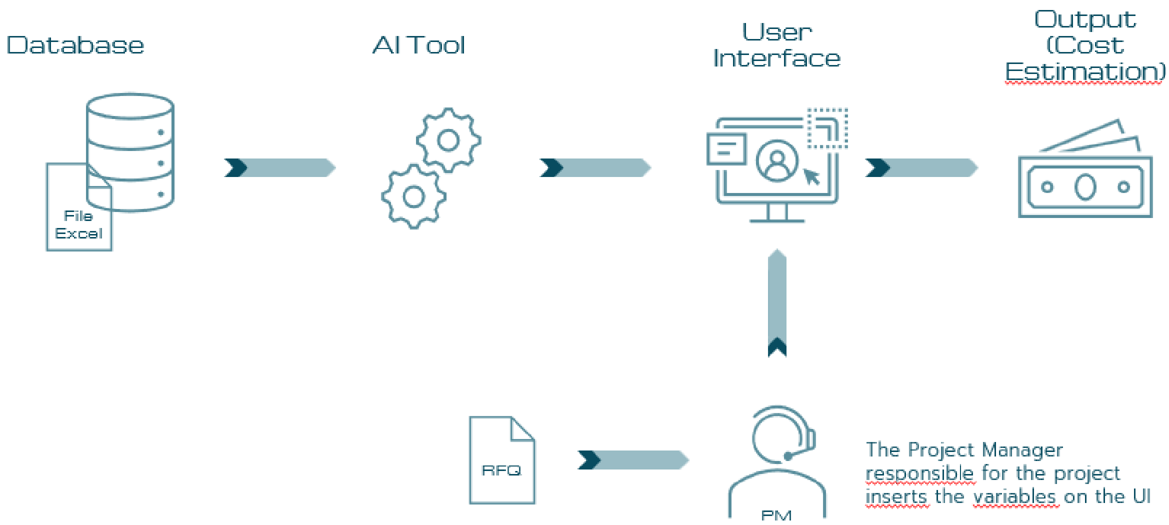

Figure 5.9: Future evolution of the tool

Chapter 6

Italdesign AI Readiness

The term AI readiness indicates how ready a company is to introduce and use AI in its processes. It's not just about having new and advanced technologies, but also organized data, people with adequate skills and flexible processes. Evaluating the level of AI readiness is essential before implementing new tools, because it allows you to understand where to intervene to obtain the best results. In the case of Italdesign, this subchapter analyzes the company's readiness to accommodate AI solutions, focusing specifically on the engineering project management department.

This means assessing on several fronts, both technological and organizational, how much the company possesses:

- a clear and concrete strategy for AI;
- an appropriate technological infrastructure;
- quality and well-managed data;
- specialized skills and talents;
- governance that supports AI adoption;
- a corporate culture open to change;

This measurement identifies strengths and weaknesses, helping to understand which actions to intervene to improve the capacity for innovation and competitiveness. In practice, it means obtaining a precise snapshot of the degree of business readiness to exploit AI as a lever for transformation and competitive advantage.

In italdesign's case AI readiness can be defined as the degree to which the organization is prepared to successfully adopt, integrate, and leverage artificial intelligence technologies in its processes. It's possible to identify three core dimensions:

- **Technological Readiness**, concerning data infrastructure, IT systems, and technical capabilities required to develop and deploy AI solutions.
- **Organizational Readiness**, related to management support, process standardization, and the alignment between business strategy and digital initiatives.
- **Cultural Readiness**, referring to the mindset, openness to innovation, and willingness of employees to collaborate with intelligent systems.

The assessment conducted in this thesis reveals that Italdesign is at an intermediate level of maturity: it has solid technological foundations and a high level of managerial awareness, but still faces challenges in data governance and in the diffusion of an AI-oriented organizational culture.

In Italdesign, the collection and organization of data relating to projects does not take place through a methodical and standardized system. There is a historical database that contains projects from past years, but its internal structure is unclear and coherent. Projects are organized primarily by client, with each client having a dedicated folder, and subsequently broken down by year of execution. However, there is no uniform formatting for collecting and storing project documents: each project manager adopts their own method for saving files, resulting in variability in the structure of documents and their findability. Furthermore, numerous documents are incomplete or missing, making historical consultation of projects even more difficult. Regarding economic information, cost and bid data are stored in a separate platform, called Appian. This platform contains elements such as bid code, estimated cost, revenue margin and other supporting data. Again, some information is incomplete and, above all, there is often a discrepancy between the projects registered in Appian and those present in the internal database. Such a situation makes it complex to find all the data and documents needed for a given project and represents a significant obstacle for the analysis and implementation of automated project management support tools.

As for AI tools, the company already has some tools that have recently been integrated into the team, for example the RFQ Assistant, which is a chatbot developed internally and trained on past projects, ready to support project managers, helping them read and analyze RFQs and also answering specific questions about new or past projects. Thanks to the RFQ Assistant, customer response times are reduced and initial information is more reliable. As is often the case in established business contexts, some team members, particularly those with more experience, show skepticism towards the chatbot and AI solutions in general. These professionals tend to prefer traditional methods of analysis and estimation, doubting the ability of the instrument to correctly interpret all the complex information contained in RFQs. This type of attitude can slow down the adoption of AI and for this reason it requires a careful approach, combining training, practical demonstration of benefits and direct team involvement to increase confidence in the tool.

At the organizational level, Italdesign exhibits strong managerial commitment toward digital innovation. The involvement of the Project Management Engineering Department in this research confirms that leadership recognizes AI as a strategic enabler of efficiency and competitiveness. However, the company still operates through siloed information flows typical of large engineering firms, where departments manage their data independently. This organizational structure slows down the diffusion of shared standards and the reuse of data across functions. During the research project, it emerged that the creation of a centralized and structured database would be a key enabler, allowing consistent integration between technical, economic, and operational data. This effort would not only facilitate AI adoption but also improve collaboration between project managers, engineers, and data scientists.
From a skills perspective, project managers possess a good understanding of processes and projects, but not all have experience in the use of advanced AI tools. In addition, there is no structured training course on artificial intelligence, and knowledge tends to be focused on a few individuals. Finally, business processes are only partially ready to integrate AI: some phases, such as pre-initiation, do not yet have adequate digital tools, and the use of AI remains limited.

Cultural readiness represents perhaps the most complex dimension. Although Italdesign's workforce shows a high level of technical expertise, awareness and trust in AI systems are still developing. Interviews and feedback from project managers highlighted both enthusiasm and caution: while many recognize the potential of AI for accelerating repetitive tasks, some express concerns about reliability, data privacy, and the risk of reducing the human role in decision-making. This ambivalence is common in organizations approaching AI for the first time. To address it, training and communication initiatives should accompany technological deployment. Workshops on AI fundamentals, data literacy programs, and the active involvement of end users in co-design phases could increase acceptance and foster confidence in AI-assisted tools.

The research project revealed several structural and methodological challenges that currently limit Italdesign's AI readiness:

- Limited dataset size and heterogeneity, restricting the training of high-performing machine learning models.
- Lack of standardized data collection protocols, leading to inconsistencies between departments.
- Absence of systematic validation procedures to benchmark algorithmic predictions against expert evaluations.
- Insufficient integration between AI tools and existing enterprise software, which hinders operational deployment.
- Need for multidisciplinary collaboration between data scientists, engineers, and project managers — a capability still in formation within the company.
- Overcoming these obstacles will require coordinated actions across technical, managerial, and cultural dimensions.

Despite these challenges, the readiness assessment highlights substantial benefits achieved during the research:

- Proof of feasibility: The prototype demonstrated that AI can be successfully applied to cost estimation in the RFQ phase, delivering consistent and interpretable results.
- Process acceleration: Estimated reductions of up to 60–70% in analysis time for new RFQs, freeing project managers for higher-value activities.

- Knowledge capitalization: Historical project data have been systematized and partially standardized, laying the foundation for future data governance initiatives.
- Innovation mindset: The project has triggered an organizational learning process and increased awareness of AI's strategic role in project management.

Looking forward, Italdesign could leverage these achievements to develop an AI roadmap, structured in progressive maturity stages — from pilot prototypes to enterprise integration — accompanied by continuous data governance improvement and workforce upskilling.

In conclusion, Italdesign's AI readiness can be characterized as emergent but promising. The company has already built essential technological capabilities and demonstrated the capacity to experiment and learn from pilot projects. The next steps should focus on:

- Establishing a data governance framework and unified digital architecture.
- Extending the internal dataset through systematic collection of cost and performance data.
- Creating a dedicated AI competence center to coordinate research, development, and training.
- Fostering an AI-friendly culture through internal communication and participatory innovation.

If these actions are pursued, Italdesign could evolve from AI exploration to AI-driven project management, positioning itself as a benchmark in the application of intelligent systems within the engineering and design sector.

Conclusions

Through the analysis carried out by this thesis, it was possible to analyze in depth the potential use of artificial intelligence as a technological support for project management processes, paying particular attention to the project initiation phase, i.e. the initial development phase of a project.

After starting from a theoretical study of the application and ascertaining its effectiveness through case studies, we then arrived at the experimental phase and the case of Italdesign, through which it was possible to demonstrate, through various experiments, the effectiveness of artificial intelligence and how it can actually contribute significantly to the development and optimization of company prices, also in order to improve decision-making efficiency, the precision of estimates and the speed of responses in complex and highly competitive contexts such as engineering.

The conceptual analysis has shown that artificial intelligence is not only limited to reproducing human activities, but that it can enhance the capabilities of the same both in analytical and operational contexts. The integration of machine learning techniques in project management allows automating repetitive tasks, identifying patterns in data that would be very complex to identify with the "naked eye" and predicting project times, costs and risks with greater reliability. These technologies, if correctly integrated into organizational processes, do not replace the role of the project manager, but amplify his skills, orienting him towards activities with a higher strategic value.

One of the major aspects that emerged from the research is the role and importance of data collection for the use of Machine Learning algorithms; data must not only be present in large quantities, but the fundamental aspect is the quality of the databases used, that is, their completeness, cleanliness and representativeness are fundamental factors that can negatively or positively influence the activity of fragmented datasets, incomplete or unstructured compromise the reliability of results and limit the ability of AI to provide useful insights. In fact, the research underlined the company's need to invest in the collection, standardization and management of data, an essential prerequisite for the development of reliable and scalable AI solutions.

The experimental application at Italdesign represented the operational heart of the research work and made it possible to translate and implement all the theoretical studies previously mentioned, from the operation and role of artificial intelligence to the role of data, which is fundamental for its use, it was therefore possible to implement a concrete solution calibrated to the real needs of the industrial context. The objective was to develop a support tool for cost estimation in the pre-initiating phase, in which the company receives and analyzes customer requests for offers (RFQs). At this stage, response time and the accuracy of economic assessments are determining factors for the competitiveness of the enterprise.
The prototype created was designed to analyze the data and information contained within the RFQs and, after drawing on the database, compare them with previous projects to provide an initial cost estimate based on historical company experience. Using machine learning techniques, the system is able to identify similarities between new and old projects, learning from existing data and returning a faster and more coherent preliminary evaluation to the project manager. This approach does not replace human judgment, but supports it, allowing analysis times to be reduced and the quality of the first estimates to be standardized.

Ultimately,the results obtained confirmed the technical feasibility and potential operational value of the proposed solution. The tool has demonstrated that it can significantly accelerate the bid evaluation process and improve the consistency of economic forecasts compared to traditional estimates. Furthermore, the experiment highlighted how the adoption of artificial intelligence models can represent, for a complex company like Italdesign, a concrete step towards the digitization of processes and the valorization of internal information assets. While requiring further developments in terms of data, integration and user interface, the project laid the foundations for the creation of a scalable system adaptable to the future needs of the Project Management department, demonstrating the strategic relevance of AI as a lever for innovation in engineering processes and management.

References

Aggrawal, S. & Dittman, K. C. (2023). "Preparing Engineers for the Future: Project Management for Developing Generative AI". *2023 Fall ASEE Mid Atlantic Conference*. doi: 10.18260/1-2--45127.

Alam, A. (2023). *What is Machine Learning?* doi: 10.5281/zenodo.8231580.

Alutbi, M. (2020). *Work Breakdown Structure*. Tech. rep. University of Thi-Qar, College of Engineering, Petroleum and Gas Department.

Anolytics (2024). *The Impact of Unrepresentative Data on AI Model Biases*.

Asana (2024). *Project Management Triangle Explained*.

Bahroun, Z. et al. (2023). "Artificial Intelligence Applications in Project Scheduling: A Systematic Review, Bibliometric Analysis, and Prospects for Future Research". *Management Systems in Production Engineering*, 31:2, 144–161. doi: 10.2478/mspe-2023-0017.

Boakye Acka, B. & Sarkodie, P.-C. K. (2024). *Generative AI and the Future of Project Management: Leveraging Generative AI for Project Management*. doi: 10.13140/RG.2.2.34732.07046.

Buchanan, B. G. (Dec. 2005). "A (Very) Brief History of Artificial Intelligence". *AI Magazine*, 26:4, 53. doi: 10.1609/aimag.v26i4.1848.

Centric Consulting (2023). *Using AI in Project Management Knowledge Management*.

Chapelle, O. et al., eds. (2006). *Semi-Supervised Learning*. MIT Press. ISBN: 9780262033589.

Costantino, F. et al. (2015). "Project selection in project portfolio management: An artificial neural network model based on critical success factors". *International Journal of Project Management*, 33:8, 1744–1754. doi: 10.1016/j.ijproman.2015.07.003.

Creole Studios (2023). *AI Enhances Software Cost Estimation Accuracy*.

English, L. (2025). *AI in Project Management: Turning Past Mistakes Into Risk Intelligence*.

Feuerriegel, S. et al. (2024). "Generative AI". *Business & Information Systems Engineering*. doi: 10.1007/s12599-023-00834-7.

Filippucci, F. et al. (2024). *The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges*. 15. OECD Publishing. doi: 10.1787/8d900037-en.

Forbes Insights (2025). *Artificial Intelligence and Lessons Learned in Projects*.

Goodfellow, I. et al. (2014). “Generative Adversarial Nets”. *Advances in Neural Information Processing Systems*. Vol. 27. Curran Associates, Inc.

Harvard Business Review (2025). *Harvard Business Review*.

Institute of Project Management Ireland (2024). *What Is a Project Life Cycle and Its 5 Stages?*

Karras, T. et al. (2017). “Progressive Growing of GANs for Improved Quality, Stability, and Variation”. *CoRR*, abs/1710.10196. arXiv: 1710.10196.

Kerzner, H. (2017). *Project Management: A Systems Approach to Planning, Scheduling, and Controlling*. 12th ed. Hoboken, NJ: John Wiley & Sons. ISBN: 9781119165354.

— (2022). *Project Management: A Systems Approach to Planning, Scheduling, and Controlling*. 13th. Hoboken, NJ: John Wiley & Sons.

Kingma, D. P., Mohamed, S., et al. (2014). “Semi-Supervised Learning with Deep Generative Models”. *Advances in Neural Information Processing Systems (NeurIPS)*. Vol. 27. Curran Associates, Inc., 3581–3589.

Kingma, D. P. & Welling, M. (2013). “Auto-Encoding Variational Bayes”. *arXiv preprint arXiv:1312.6114*.

Lana, A. (2023). *Corriere della Sera*.

Leitch, R. (1992). “Artificial intelligence in control: some myths, some fears but plenty prospects”. *Computing & Control Engineering*, 3:4, 153–163.

Lorenz, P. et al. (2023). *Initial Policy Considerations for Generative Artificial Intelligence*. 1. Paris: OECD Publishing. doi: 10.1787/fae2d1e6-en.

Mangal, A. (2023). “Revolutionizing Project Management with Generative AI”. *ESP Journal of Engineering & Technology Advancements*, 3:4, 53–60. doi: 10.56472/25832646/JETA-V3I8P106.

Mohammed, S. et al. (May 2025). “The Effects of Data Quality on Machine Learning Performance on Tabular Data”. *arXiv preprint*, arXiv:2207.14529.

Morales, E. F. & Escalante, H. J. (2022). *Machine Learning: With Applications in Information Security*. Elsevier. doi: 10.1016/B978-0-12-820125-1.00001-1.

Odejide, O. & Edunjobi, S. (2024). "Artificial intelligence in project portfolio management: Enhancing project selection and decision-making". *International Journal of Project Organisation and Management*, 16:2, 101–118.

Project Management Institute (2017). *A Guide to the Project Management Body of Knowledge (PMBOK Guide)*. 6th. Newtown Square, PA: Project Management Institute.

— (2023). *Shaping the Future of Project Management With AI*.

— (2024). *What is Project Management?*

Project Management Institute Sweden Chapter (2024). *Navigating AI in Project Management: A PMI Chapters Collaboration Case Study Report*.

ProjStream (July 2024). *The Future of Cost Estimating: Embracing AI and Machine Learning*.

Radford, A. et al. (2019). *Language Models are Unsupervised Multitask Learners*. Tech. rep. OpenAI.

Riguzzi, F. (2006). *Introduzione all'Intelligenza Artificiale*. Apogeo Education. ISBN: 1511.04352.

Salimimoghadam, M. et al. (2025). "Chatbot-based stakeholder engagement in AI-enabled project management". *International Journal of Project Innovation*, 12:1, 55–72.

Shamim, M. M. I. (2024). "Artificial Intelligence in Project Management: Enhancing Efficiency and Decision-Making". *International Journal of Management Information Systems and Data Science*, 1:1, 1–6.

Shamim, M. M. I. et al. (2025). "Advancement of Artificial Intelligence in Cost Estimation for Project Management Success: A Systematic Review". *Modelling*, 6:2, 661–669, 679–687, 750–758.

Sharma, R. et al. (2020). "Study of Supervised Learning and Unsupervised Learning". *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*. doi: 10.22214/IJRASET.2020.6095.

Smola, A. J. & Vishwanathan, S. V. N. (2008). *Introduction to Machine Learning*. Cambridge University Press. ISBN: 52182583.

Sutton, R. S. & Barto, A. G. (2018). *Reinforcement Learning: An Introduction*. Second. The MIT Press.

Tan, J. B. B. et al. (2021). "Project Reporting Management System with AI-based Assistive Features for Text Summarization". *International Journal of Machine Learning and Computing*, 11:1, 21–27. doi: 10.18178/ijmlc.2021.11.1.1009.

Vaswani, A. et al. (2017). "Attention Is All You Need". *Advances in Neural Information Processing Systems (NeurIPS)*. Vol. 30. Curran Associates, Inc.

Wang, X. et al. (2025). "Research on Clustering Analysis of Generative AI Tool Usage Behaviors Among College Students".

Wauters, M. & Vanhoucke, M. (2016). "A comparative study of Artificial Intelligence methods for project duration forecasting". *Expert Systems with Applications*, 46, 249–261. doi: 10.1016/j.eswa.2015.10.008.

Weng, J. (2023). *Putting Intellectual Robots to Work: Implementing Generative AI Tools in Project Management*.

Witten, I. H. et al. (2017). *Data Mining: Practical Machine Learning Tools and Techniques*. 4th ed. Morgan Kaufmann. ISBN: 9780128042915. doi: 10.1016/C2009-0-19715-5.

Zou, Y. et al. (2017). "Retrieving similar cases for construction project risk management using natural language processing techniques". *Automation in Construction*, 80, 66–76. doi: 10.1016/j.autcon.2017.04.003.

Acknowledgements

This thesis marks the end of a journey that has been long, demanding, and full of ups and downs, a journey that I often thought would never begin, but that I now find myself reluctant to see end. What do I miss? Certainly not the exams, the stress, or the tears (of which, believe me, there were many).

First and foremost, I would like to express my sincere gratitude to my supervisor, **Professor Filippo Maria Ottaviani**, and to my co-supervisor and company tutor, **Matteo Leschiera**, for their constant guidance and support throughout this final stage of my academic path. I also wish to thank the entire Italdesign team for welcoming me and making me feel part of the group from day one.

This journey has given me the opportunity to meet extraordinary people, true and genuine friends with whom I could laugh even during the most tragic pre-exam moments, but especially in the quiet ones: during lectures, between classes, at lunch breaks, or in the evenings wandering around Turin. It never really mattered where we were, as long as I was with them. So, I am grateful for the choice I made five years ago, because it led me to meet **Alice**, **Martina**, **Beatrice (Bri)**, and **Giovanni**. You should know that you're not getting rid of me anytime soon. Many other wonderful people, both from my bachelor's and master's degrees, will forever have a place in my heart. I love you all dearly.
Moreover, like an unexpected winter ray of sunshine, **Lia, Ludovica, Elisabetta, and Federica** appeared during the last semester of my final year at the Politecnico di Torino. I am so grateful that circumstances allowed us to meet and grow closer, becoming friends in such a short time.

A heartfelt thank you to my **Pupa**, a pure soul who has been by my side for so many years, always supporting my decisions and making me laugh no matter what. I still don't know what

I did to deserve you in my life.

I am deeply thankful to my **parents**, for allowing me to pursue this academic path without financial worries, carrying those burdens themselves so I could focus entirely on my studies. To my **mother** in particular, thank you for never underestimating my abilities, for pushing me to follow my heart, and for encouraging me to always give my best.

A very special thank you goes to **Amedeo**. It's hard to put into words what you mean to me, because it's simply beyond description. What I can say is that you are the kindest, funniest, most generous, gorgeous and selfless person I've ever known. You have always been my strength and my sunshine on dark days and you inspire me to be a better person. You celebrated my victories, lifted me after my defeats, and never doubted my abilities. You are my number one fan and I am yours, forever.

Lastly, but by no means least, I want to thank my little twin sister, **Ester**. Without you, these years would not have been nearly as wonderful. Your patience and willingness to help me study, even at the cost of your own time, gave me the strength to keep going and never give up. I love you, and I always will, no matter where in the world you are.