SOPHIA LEAL CODOGNOTTO

LARGE LANGUAGE MODELS ADOPTION IN PROJECT MANAGEMENT: APPLICATIONS, BENEFITS, AND CHALLENGES IN ORGANIZATIONS

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LARGE LANGUAGE MODELS ADOPTION IN PROJECT MANAGEMENT: APPLICATIONS, BENEFITS, AND CHALLENGES IN ORGANIZATIONS

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To my beloved family, with gratitude for their lifelong support and encouragement.

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RESUMO

Modelos de linguagem de grande escala (LLMs) estão sendo incorporados às práticas de gestão de projetos em organizações com diferentes níveis de maturidade. Este trabalho tem como objetivo identificar suas principais aplicações, benefícios percebidos e desafios emergentes em contextos de projetos. A pesquisa combina uma revisão de literatura não sistemática, que evidencia a rápida expansão de estudos sobre IA generativa na gestão de projetos, com uma investigação empírica qualitativa baseada em entrevistas semiestruturadas conduzidas com cinco empresas de diferentes portes e setores. Por meio de codificação aberta e axial, foram identificadas dezessete categorias de aplicações de LLMs, abrangendo automação de tarefas operacionais, suporte à comunicação e colaboração, gestão e expansão de conhecimento, processos de inovação e ideação, treinamento e desenvolvimento, além de elaboração de relatórios e documentação. Nove benefícios emergiram da análise, sendo economia de tempo e custo, ganhos de produtividade e eficiência e melhoria da qualidade das entregas citados de forma unânime em todos os casos. Os resultados também revelam desafios técnicos, estruturais e culturais que condicionam a adoção, tais como lacunas de competências e baixa proficiência em IA, riscos de dependência excessiva e interpretação inadequada de resultados, ausência de indicadores qualitativos, preocupações relacionadas à segurança cibernética e privacidade, integração limitada com sistemas e resistência a mudanças. O estudo contribui para a teoria ao identificar códigos emergentes pouco discutidos na literatura existente, como padronização e indicadores qualitativos limitados, e ao evidenciar lacunas entre expectativas teóricas e a prática organizacional. Para profissionais de gestão de projetos, os resultados demonstram que a adoção efetiva de IA depende de estruturas claras de governança, ambientes internos de IA seguros, desenvolvimento contínuo de capacidades e modelos híbridos de colaboração humano-IA.

Palavras-chave: Inteligência artificial. Inteligência artificial generativa. Modelos de linguagem de grande escala. Gestão de projetos. Adoção.

ABSTRACT

Large language models (LLMs) are being incorporated into project management practices across organizations with varying levels of maturity. This work has the objective of identifying their main applications, perceived benefits, and emerging challenges in project contexts. The research combines a non-systematic literature review, which highlights the rapid expansion of studies on generative AI in project management, with a qualitative empirical investigation based on semi-structured interviews with five companies of different sizes and industries. Through open and axial coding, seventeen categories of LLM applications were identified, including operational task automation, communication and collaboration support, knowledge management and expansion, innovation and ideation processes, training and development, and reporting and documentation. Nine benefits emerged from the analysis, with cost and time savings, productivity and efficiency gains, and improved delivery quality cited unanimously across all cases. The findings also reveal technical, structural and cultural challenges that condition adoption, such as skills gaps and limited AI literacy, risks of overreliance and misinterpretation of outputs, lack of qualitative indicators, cybersecurity and privacy concerns, limited system integration, and resistance to change. The study contributes to theory by identifying emergent codes not widely discussed in existing literature, such as standardization and limited qualitative indicators, and by highlighting gaps between theoretical expectations and organizational practice. For project management professionals, the results demonstrate that effective AI adoption depends on clear governance structures, secure AI environments, continuous capability development, and hybrid models of human-AI collaboration.

Keywords: Artificial intelligence. Generative artificial intelligence. Large language models. Project management. Adoption.

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LIST OF ABBREVIATIONS AND ACRONYMS

LLM	Large Language Models
PM	Project Management
AI	Artificial Intelligence
PMO	Project Management Officer
PMBOK	Project Management Body of Knowledge
PMI	Project Management Institute
GenAI	Generative AI
ML	Machine Learning
DL	Deep Learning
RE	Requirements Engineering
BIM	Building Information Modeling
AEC	Architecture, Engineering, and Construction
GT	Grounded Theory

SUMMARY

1 INTRODUCTION

This Thesis Project was developed jointly between the Escola Politécnica da Universidade de São Paulo (USP) and the Politecnico di Torino, as part of a dual-degree engineering program that integrates academic training, applied research, and international collaboration. The motivation for the study emerged from the converging interests of research groups from both institutions and this chapter presents the objective of the thesis, as well as a brief explanation of the structure of the research.

1.1 Problem Existence and Importance

The accelerating advancement of Artificial Intelligence (AI), particularly through Generative AI (GenAI) and Large Language Models (LLMs), is transforming how organizations conceptualize and execute projects across industries. As noted by the Project Management Institute (PMI), we are now living in an Exponential Age, where "AI is rocking every industry and every profession—from IT to the creative arts to manufacturing and, yes, to project management" (PMI, 2024). This technological leap challenges traditional project management (PM) practices that have historically relied on manual coordination, human judgment, and retrospective analysis.

While AI has been progressively incorporated into project tools for automation and analytics, the introduction of LLMs such as ChatGPT, Gemini (formerly Bard), Claude, and Copilot has revolutionized the cognitive dimension of project work. These systems are capable of understanding and generating natural language, synthesizing information from complex documentation, and supporting managerial decision-making. According to the 2023 PMI Annual Global Survey on Project Management, 21% of global project professionals already use AI tools frequently, and over 80% of senior leaders anticipate AI to have a significant impact on project execution within the next five years (PMI, 2023).

Despite this momentum, most organizations struggle to translate AI's potential into consistent project performance improvements. Project delays, cost overruns, and communication breakdowns remain prevalent (PMI SWEDEN, 2024). At the same time, the volume of unstructured project data (emails, reports, requirements documents) continues to grow exponentially, overwhelming traditional management methods. This context highlights the need for intelligent, language-based systems that can analyze, summarize, and contextualize project information, supporting human decision-making while reducing cognitive workload (PMI, 2024).

The growing importance of this problem is further underscored by cross-sectoral research. Studies in construction, software, and risk management demonstrate that LLM-based systems can increase accuracy, improve communication, and facilitate knowledge retention (CHO; PARK; LEE, 2023; ZHANG; GE, 2025; CHOU; CHONG; LIU, 2024).

1.2 Research Gap

Despite the growing body of research, the empirical understanding of how Large Language Models (LLMs) can be systematically integrated into project management processes, from initiation to closure, remains limited. The topic, in its current form, is still emerging globally, as both academia and industry work to understand its practical implications.

Organizations across sectors exhibit varying levels of maturity in adopting and operationalizing these technologies, reflecting an ongoing process of experimentation and adaptation. Companies are only beginning to delineate the specific applications, measurable benefits, and inherent challenges of LLM deployment in real project environments, highlighting the need for structured, evidence-based studies to guide their effective and responsible implementation.

1.3 Objective

Given the above gaps, this research aims to analyze and conceptualize how Large Language Models can enhance the efficiency, adaptability, and knowledge management capacity of project management across industries by examining the applications, benefits, and challenges associated with LLM adoption within the project management life cycle, synthesizing academic and professional perspectives.

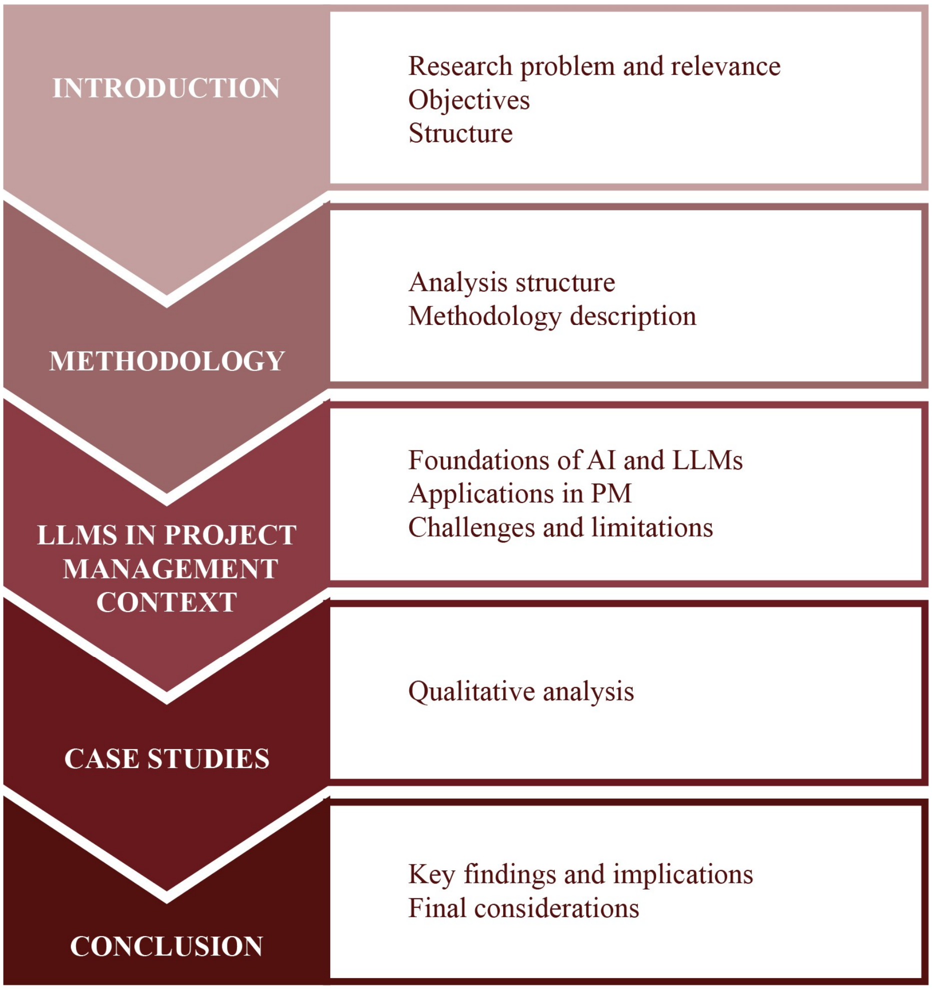
Specific objectives include:

a) to define the theoretical and technological foundations of AI, GenAI, and LLMs relevant to project management;
b) to identify and categorize existing applications of LLMs in PM functions such as planning, risk management, scheduling, and communication;
c) to evaluate the main benefits and challenges associated with their adoption.

1.4 Structure

This thesis is organized into five main chapters, each building upon the previous to provide a coherent understanding of how Artificial Intelligence, particularly Large Language Models (LLMs), is transforming the field of project management, as shown in Figure 1.

Figure 1 - Thesis structure



Source: Created by the author.

Chapter 1 introduces the research problem, establishes its relevance, reviews the evolution of literature on AI and project management, and defines the study's objectives and scope. It also presents the overall structure of the thesis and highlights the rationale for investigating LLMs as a disruptive force in contemporary project environments.

Chapter 2 describes the Methodology adopted for the study. It outlines the research design, data collection methods, and analytical procedures used to investigate the integration of LLMs into project management practice. The chapter details the rationale for selecting case studies, the qualitative and quantitative instruments applied, and the approach to consolidating findings.

Chapter 3 presents the Literature Review of LLMs in Project Management context, which consolidates three interconnected analytical dimensions that were previously separated. It begins by outlining the foundations of Artificial Intelligence and Large Language Models, detailing their architectures, mechanisms, and evolution from traditional machine learning approaches. The chapter then explores the applications of AI and LLMs in project management across the project life cycle, including initiation, planning, execution, monitoring, and closure, using evidence from recent empirical studies in software, construction, and engineering domains. Finally, it discusses the challenges and future trajectories associated with these technologies, covering ethical risks, cybersecurity, data governance, and the evolving role of project managers in AI-augmented environments. Together, these sections form a comprehensive theoretical framework supporting the research.

Chapter 4 presents the Case Studies, examining the empirical evidence gathered through the selected cases, highlighting how LLM-based tools were applied in real project contexts, their observed benefits, and the challenges encountered. This chapter connects theoretical insights from the literature review with practical observations, providing a grounded understanding of the role of LLMs in enhancing project management effectiveness.

Finally, Chapter 5 presents the Conclusion, summarizing the key findings of the research and their implications for both theory and practice. The chapter also identifies limitations of the present study and outlines directions for future research aimed at advancing the intersection of AI and project management.

2 METHODOLOGY

This chapter aims to describe the methodological procedures adopted in this study. The research was conducted through a combination of literature review, interviews with companies from different sectors, and qualitative data analyses. Together, these methods provide a comprehensive framework for exploring the research objectives and validating the proposed conclusions. Considering the objectives mentioned in the first chapter, the questions proposed by this research are:

- Q1: What are the main applications of Generative AI and LLMs in Project Management?
- Q2: What are the main benefits of these applications?
- Q3: What are the main challenges faced by the companies when applying AI?

To answer those questions, the work was structured in 4 main phases, shown in Figure 2:

Figure 2 - Research Methodology

Source: Created by the author.

The methodological design of this Thesis Project was inspired by two previous graduation works (KOBAYASHI, 2022; HIRATA, 2022), whose analytical structure and research procedures informed and guided the development of the present study.

2.1 Literature Review

A comprehensive designed literature review plays a foundational role in any academic research, particularly in studies exploring emerging technologies such as Artificial Intelligence (AI) and Large Language Models (LLMs) in project management. The main objective of this stage was situating the current investigation of AI within the broader body of knowledge of PM, identifying theoretical foundations, empirical evidence, and existing research gaps.

The search for existing literature was conducted in a non-systematic manner, aiming to identify the most relevant publications on the application of Artificial Intelligence (AI) and Large Language Models (LLMs) in project environments, without the constraint of reviewing all available studies. The initial literature search conducted in Web of Science identified 136 articles published between 2012 and 2025. The growing number of publications in recent years

(120 articles after 2021) highlights the increasing scholarly interest in AI-enabled project practices.

An initial screening was carried out based on the abstracts of the retrieved papers, resulting in the selection of twenty key articles that provided the most significant insights aligned with the research focus. These primary studies led to the inclusion of additional sources through reference tracing and complementary searches related to recurring themes in the literature. Furthermore, the review incorporated industry reports, institutional publications, and materials from leading organizations and project management institutes, thereby ensuring a comprehensive understanding of AI from multiple perspectives. Following the selection of all sources, a content analysis was performed, culminating in the development of a summary table that synthesizes the main applications of AI in project management.

2.2 Field Research

The field research was conducted with companies from diverse sectors that employ Artificial Intelligence (AI) in project management at varying levels of maturity. Through a series of semi-structured interviews, the study aimed to identify the main applications, benefits, and challenges associated with the implementation of AI in project environments, with the objective of comparing these empirical findings with insights drawn from the literature review.

2.2.1 Case selection

For analytical purposes, five companies engaged in project-based activities and already employing Artificial Intelligence (AI) in their operations were selected. The sample comprised organizations with different levels of market experience and operating across diverse sectors.

Table 1 below presents the profile of the selected companies and their respective sectors of operation.

Table 1 - Characterization of the selected companies

Company ID	Year of Foundation	Number of employees	Main products and services
C01	1992	~ 200	Systems integration company that offers solutions related to research, consulting and implementation, focused in automation
C02	1977	~18k	Beauty and cosmetics group that has many brands related to this sector
C03	2003	> 1k	Consulting company that evolved their technical consulting model into a business transformation and development model
C04	1996 (in Brazil)	> 2k in Brazil (60k globally)	Operates mainly in the sectors of sustainable infrastructure and renewable energy
C05	2022	> 50	Fintech company that provides payment solutions for large enterprises

Source: Created by the author.

2.2.2 Data collection

The interviews were conducted with employees nominated by company leaders for their knowledge of AI applications within their organizations. Additional information regarding the interviewees, the platform used, and the duration of each interview is provided in Table 2.

Table 2 - Interviewees' profile

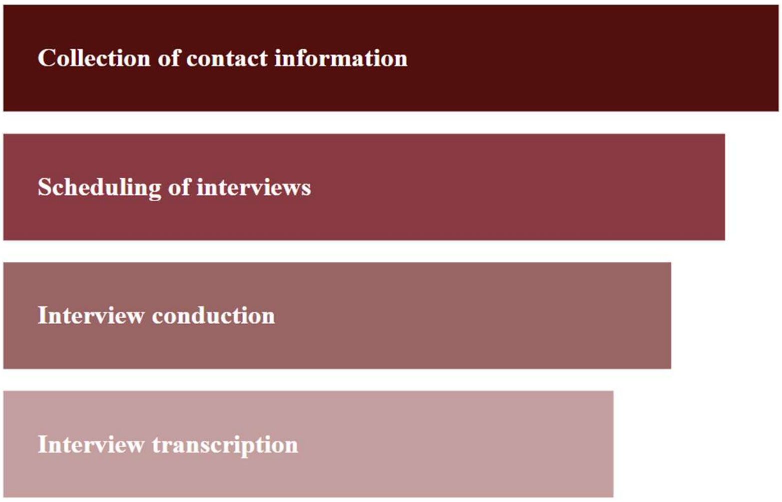
Interviewee ID	Role	Time in the company	Platform and duration
I01	Automation Project Manager	17 years	Google Meet 37 min
I02	Product Manager	2 years	Google Meet 32 min
I03	Project Manager (Consultant)	4 years	Google Meet 56 min
I04	HSE Manager	5 years	Google Meet 45 min
I05	Software Engineer	1 year	Whatsapp Asynchronous

Source: Created by the author.

The interviews were conducted remotely, either via video call or text messaging, following a semi-structured protocol presented in Appendix B. The script was designed to first explore the company's and interviewee's background (based on prior online research) and, during the interview, to gather an overall understanding of AI in project management, including the depth and dynamics of its use within the organization, as well as questions related to the perceived benefits, main challenges, and limitations of AI adoption.

All interviews were transcribed for subsequent qualitative content analysis through coding using the NVivo software, as detailed in the following section. Figure 3 illustrates the stages for data collection.

Figure 3 - Planned stages for data collection



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2.3 Qualitative Analysis

Qualitative analysis serves as the methodological foundation of this study, given that the topic of GenAI is relatively new and there is still limited quantitative evidence on how companies are using it and what indicators reflect its benefits and challenges in project management.

The analysis was based on the Grounded Theory (GT) methodology, which involves a set of systematic procedures for data analysis designed to promote greater complexity and integration. The key stages are: defining the research problem or guiding questions to initiate the investigation; selecting a sample of cases that will serve as the objects of analysis; categorizing the collected information through systematic coding procedures that require ongoing questioning and relational reflection on the intended meaning; conducting iterative refinement processes; and, ultimately, constructing analyses and theoretical insights based on the progressive development of meaning (FERNANDES; MAIA, 2001).

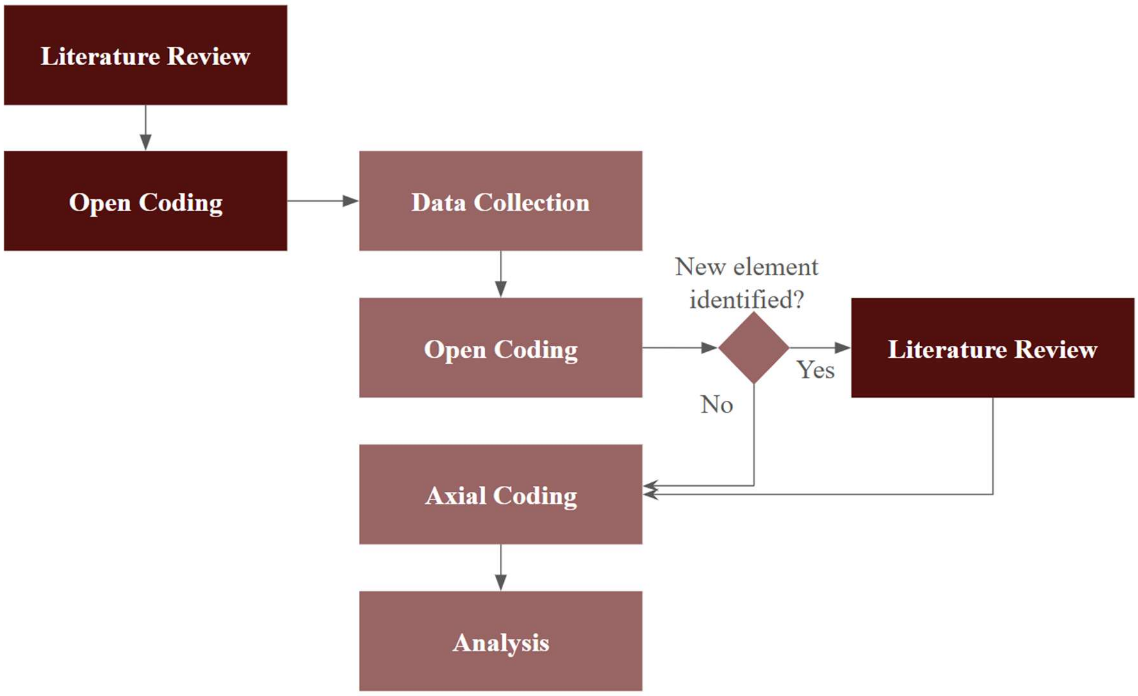
2.3.1 Data coding and analysis

The coding process mentioned in the above section has some possible formats. This work followed an open and axial coding, using the platform N-VIVO. During open coding, each data segment was labeled according to its relation to AI applications, benefits, and challenges. These initial codes were then integrated during axial coding to form higher-order categories, based on the relationships and patterns identified among the labels.

The open coding was used for the literature review coding, focusing on 3 aspects: applications. benefits and challenges of AIs, in order to find some groups that characterize the main topics. The literature review code was the ground to build the interview protocol, in order to organize the most important questions used to collect the information needed for answering Q1, Q2 and Q3 of this research.

After the transcription of each interview, the same coding process was applied to the empirical data, starting from the list of codes that were already identified in the literature and adding some relevant new ones as identified. Thus, the coding of interview data complements the theoretical framework. When new concepts emerge, additional literature is reviewed as necessary to ensure the comprehensiveness of the study. This process is illustrated in Figure 4.

Figure 4 - Data Coding Process



Source: Created by the author.

3 LARGE LANGUAGE MODELS (LLMS) IN PROJECT MANAGEMENT CONTEXT

In order to establish a comprehensive understanding of the existing research, a literature review was conducted on artificial intelligence, with particular emphasis on Large Language Models and their applications in project management.

3.1 Foundations of Artificial Intelligence and Large Language Models (LLMs)

This section establishes the necessary technological context, defining what LLMs are, the most popular tools and the mechanisms that enable their use in Project Management.

3.1.1 Definition of Artificial Intelligence and Generative AI

The Project Management Institute (PMI) defines AI as the ability of machines to exhibit behaviors traditionally associated with human intelligence, perceiving their surroundings, learning from experience, making autonomous decisions, and engaging in natural communication (PMI, 2024). AI systems can emulate human thought processes and handle repetitive tasks using extensive data (ONATAYO *et al.*, 2024). The intellectual origins of AI date back to the 1955 Dartmouth Conference, where John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon proposed that human learning and reasoning could be formally described and simulated by machines.

Generative AI (GenAI) is a specific and vital subset inside a bigger domain of AI (PMI, 2024). The adjective "generative" refers to an AI system's capacity to autonomously create new content without direct human involvement. This generated content can take various forms, including text, image, audio, or video (AL NAQBI; BAHROUN; AHMED, 2024). Over time, AI has transitioned from symbolic and rule-based systems to machine learning and deep learning paradigms that extract and generalize patterns from vast datasets. This transformation has been driven by exponential growth in computational capacity and data availability, situating contemporary society within what PMI calls the “Exponential Age”; a period in which digital, cognitive, and generative technologies converge to accelerate professional change and human–machine collaboration (PMI, 2024).

The ongoing development of AI seeks not merely to replicate but to extend human creativity and innovation, enhancing decision-making and problem-solving across domains, ultimately aiming to better serve humanity. In this context, generative AI is more than just a new technology tool; it is a transformative engine that redefines not only how individuals live and work but also expands the boundaries of professional practice and opens new possibilities for productivity and strategic foresight in work environments (AL NAQBI; BAHROUN; AHMED, 2024).

3.1.2 Large Language Models: Core concepts and Tools

Large Language Models (LLMs) are the most famous GenAI solutions currently available in the market. They can be defined as trained foundation models; deep learning neural network models configured to generate text from prompts which is understandable for humans. LLMs use large datasets to interpret, summarize, create and forecast new content. (PMI, 2024). LLMs generally represent a group of language models that empower neural networks with billions of parameters (MAHBUB *et al.*, 2016).

The main capabilities of LLMs derive from their construction process. LLMs are trained on huge amounts of unlabeled data using self-supervised learning techniques (MAHBUB *et al.*, 2016). They are developed using vast and heterogeneous datasets that encompass materials such as online content, books, and academic publications. This extensive training equips them with advanced abilities to comprehend and produce human language accurately. Consequently, these models can function as cognitive agents capable of interpreting natural language inputs, engaging in interactive dialogue, and executing tasks that depend on contextual and semantic understanding (CINKUSZ; CHUDZIAK; NIEWIADOMSKA-SZYNKIEWICZ, 2025).

LLMs are an advancement fueled by Deep Learning algorithms. The "depth" in DL models is attributed to their capability to deal with complex datasets, including unstructured and unlabeled data, without requiring human oversight or manual guidance (LI *et al.*, 2024).

The transformer architecture was a significant advancement in the field of AI, introduced by the famous paper “Attention is all you need” by Google researchers (VASWANI *et al.*, 2017). These new models are superior in quality, since it gives the ability of in-context learning, improving their comprehension of language nuances and relationships, requiring substantially less training time. The transformer architecture enables LLMs to capture long-range relationships within text, producing outputs that are more coherent and contextually appropriate (CHANG *et al.*, 2018).

LLMs thus extend beyond linguistic generation to act as reasoning engines capable of multi-domain problem solving. They demonstrate potential not only in knowledge synthesis but also in tasks requiring abstraction, analogy, and iterative learning; attributes traditionally reserved for human expertise.

The incorporation of advanced tools and methodologies has become crucial for handling the growing complexity and scale of contemporary software systems (CINKUSZ; CHUDZIAK; NIEWIADOMSKA-SZYNKIEWICZ, 2025). The most widely adopted GenAI solutions are driven by LLMs, such as ChatGPT from OpenAI, Gemini (known before as Bard) from Google, Copilot from Microsoft, Claude from Anthropic, or Llama from Meta (PMI, 2024; NI *et al.*, 2025).

3.2 LLM Applications and Capabilities in Project Management (PM)

According to the 2023 PMI Annual Global Survey on Project Management, 21% of respondents reported using artificial intelligence either consistently or frequently in the management of their projects. Large Language Models are currently being applied across all traditional phases of project management. Each phase benefits differently from LLM-based tools and generative AI systems, with varying degrees of maturity and adoption across them.

3.1.1 Initiation and Requirements Engineering

The initiation phase of a project marks the transition from an abstract idea into a formally defined endeavor, where objectives, constraints, and success criteria are first articulated (PMI, 2024). In this early stage, the integration of Large Language Models (LLMs) has emerged as a valuable support mechanism for project ideation, stakeholder identification, and the preliminary definition of scope and deliverables (PMI, 2023). Generative AI systems, particularly those based on LLM architectures such as GPT-4, can generate structured documents like project charters, synthesize feasibility studies, and identify strategic alignments between project goals and organizational priorities (PMI, 2024). By processing vast and diverse datasets, LLMs are capable of recognizing semantic relationships in textual information, which enables project managers to accelerate the translation of strategic intents into actionable plans (PMI, 2023).

GenAI and LLMs can automate the creation of fundamental project documents, such as the Project Business Case and Documentation. The creation of a Business Case is classified as a complex and strategic task where GenAI can augment human capability (PMI, 2024). In addition, LLMs can generate comprehensive project documentation adhering to industry standards and regulations, including scope, resource availability, and constraints, by providing an effective prompt with all information needed (ONATAYO *et al.*, 2024).

In addition to their use for text generation, LLMs have also been applied to enhance conceptual design reasoning in the earliest phases of project definition. The Knowledge-Augmented Generalizer–Specializer (KAGS) framework proposed by Sahadevan *et al.* (2025) illustrates this capability by using LLM-driven semantic reasoning to automate problem formulation, identify relevant parameters, and map dependencies between project variables. This approach supports the cognitive aspects of early project exploration by enabling explainable reasoning and transparent documentation of initial design decisions (SAHADEVAN *et al*., 2025).

The requirements engineering (RE) phase represents the next critical step in transforming the conceptual definition of a project into detailed and verifiable requirements (PMI, 2023). Traditional approaches to requirements elicitation and specification are often hindered by ambiguities, inconsistencies, and omissions in documentation. The advent of LLMs introduces new possibilities for improving the precision and overall quality of requirements. Detecting inconsistencies or errors at an early stage of documentation serves as an essential approach to reducing costs and saving time throughout the project lifecycle (MAHBUB *et al.*, 2016). LLMs such as GPT-4 have been examined for their effectiveness in identifying key defects. Although human evaluation is still required to discern and eliminate irrelevant or incorrect "false positives", these models can rapidly analyze documentation and highlight potential issues with high efficiency (MAHBUB *et al.*, 2016).

Gaona-Cuevas, Bucheli-Guerrero, and Vera-Rivera (2024) developed the Smart Product Backlog model, in which supervised machine learning and LLM-based classification automatically distinguish between AI and Non-AI user stories. This model assists agile teams in prioritizing user stories and assessing their technical feasibility for AI implementation (GAONA-CUEVAS; BUCHELI-GUERRERO; VERA-RIVERA, 2024).

In construction projects, designers must evaluate numerous considerations, such as financial constraints, site conditions, design specifications, and environmental legislation, to make informed, sustainability-oriented decisions. To manage this complexity, optimization frameworks like mixed-integer programming and GPT-based models integrated with Building Information Modeling (BIM) have emerged as effective tools for performing detailed assessments and generating environmentally conscious design alternatives. A key application of text-to-text generative AI in the pre-construction phase lies in its ability to compile comprehensive feasibility studies. By analyzing large datasets and producing concise, actionable insights, this technology streamlines decision-making, enabling stakeholders to pursue solutions aligned with sustainability objectives. Additionally, generative AI contributes to ensuring regulatory compliance by automating documentation according to current environmental standards and supports the creation of persuasive proposals and bids, both essential for project approval and subsequent execution (ONATAYO *et al*., 2024).

Overall, the use of LLMs in project initiation and requirements engineering promotes a more structured, intelligent, and transparent approach to early-stage project definition. Their capacity to interpret natural language, generate coherent documentation, and reason about contextual relationships positions these systems as indispensable assistants in managing complexity from the very beginning of the project lifecycle (PMI, 2023).

3.2.2 Planning Phase

The planning phase is one of the most critical moments in project management, as it defines the roadmap that will guide all subsequent activities and decisions. Artificial Intelligence (AI) and, more recently, Large Language Models (LLMs), have played an increasingly prominent role in this stage, supporting project professionals in developing schedules, estimating costs, managing risks, and optimizing resources (PMI, 2024). The Project Management Institute highlights that AI enhances the precision of planning processes by automating data analysis, forecasting trends, and generating preliminary plans based on historical information and real-time inputs (PMI, 2023). These systems not only process large datasets but also integrate qualitative information expressed in natural language, enabling a deeper understanding of stakeholder expectations and contextual variables that influence project success (PMI, 2024).

As mentioned in the section Initiation and Requirements Engineering, studies from Mahbub *et al.* (2016) and Gaona-Cuevas, Bucheli-Guerrero, and Vera-Rivera (2024) showed that LLMs contribute to requirements analysis and documentation and also prioritization of user stories. These approaches reduce human error and allow planning teams to focus on high-value analytical and strategic decisions.

GenAI can examine both current project information and historical organizational data to customize project management approaches and methodologies that align with the project's particular requirements, ultimately producing a coherent project management plan (PMI, 2024; ONATAYO *et al*., 2024). This process entails adopting a holistic perspective that integrates organizational capabilities with the unique attributes of each project (PMI, 2023).

One important task in project management is the Portfolio management and Project prioritization. When managing multiple concurrent projects, LLMs assist in prioritizing work through a data-driven analysis of criteria such as return on investment and success potential. Through predictive analytics, AI systems can rapidly generate a ranked hierarchy of project tasks according to predefined evaluation criteria, thereby supporting objective and strategic prioritization (PMI, 2024; PMI SWEDEN, 2024).

LLMs streamline the creation and optimization of project schedules and resource plans, addressing complexities arising from multiple teams and shared constraints. AI-generated schedules can be developed, optimized, and smoothly incorporated into project management workflows, significantly reducing the time and effort required compared to traditional manual scheduling (ONATAYO *et al*., 2024). In this context, one study demonstrated the effectiveness of ChatGPT in producing logical and requirement-compliant project schedules and task sequences (PRIETO *et al*., 2023). LLM-powered agents can automate the creation of schedules based on project milestone dates and resource availability, accounting for multiple teams across business units and shared resources (PMI, 2024).

The Multi-Agent LLMs-driven Evolutionary Framework for Scheduling Optimization (MAEF) introduces an innovative approach that leverages multiple LLM-based agents to address complex scheduling challenges, including Resource-Constrained Project Scheduling. Within this framework, different agents are assigned specialized roles such as generating an initial, diverse set of feasible candidate solutions and performing evolutionary optimization through genetic operations like selection, crossover, and mutation, enabling iterative refinement toward high-quality, optimized schedules (WANG; WANG; CHU, 2025).

AI can evaluate project requirements, existing organizational capabilities, and potential interdependencies to design an optimized resource management plan (PMI, 2024; PMI SWEDEN, 2024). In addition, specialized AI systems enhance resource allocation by delivering real-time analytical insights, thereby facilitating more adaptive budgeting processes and dynamic portfolio management strategies (CINKUSZ; CHUDZIAK; NIEWIADOMSKA - SZYNKIEWICZ, 2025; PMI SWEDEN, 2024).

Effective cost management is a central component of project planning, as it establishes the financial boundaries within which the project objectives can be achieved. Every project requires a cost management plan that defines the scope of expenditure and identifies the activities that can be executed within the approved budget. In this context, Artificial Intelligence (AI) systems, particularly those employing Large Language Models (LLMs), can substantially enhance the efficiency and precision of cost planning activities (PMI, 2024). Beyond prediction, AI-driven tools assist project practitioners in automating essential financial management tasks, such as compiling approval requirements, identifying available funding sources, and generating the documentation necessary for budget authorization and reporting (PMI, 2023). The integration of these capabilities streamlines cost planning processes, minimizes human error, and promotes financial transparency throughout the planning phase, allowing project managers to make more informed and timely investment decisions (PMI, 2024).

Other research has proposed an innovative approach using Bidirectional Encoder Representations from Transformers (BERT) and an automated model that uses natural language processing (NLP), to extract relevant insights from bid and change-order documents. By comparing textual data from past projects, the model predicts potential cost and schedule variations in new initiatives with over 75% accuracy (SHRESTHA; KO; LE, 2025). This predictive capability enables planners to anticipate and mitigate deviations before execution begins, fostering proactive management of budget and timeline constraints. The same methodology has also been applied to the automatic detection of contractual risk clauses in construction documentation (SHRESTHA; KO; LE, 2025).

Another major field of application is risk management, an essential component of the planning process. Studies indicate that LLMs can assist in identifying, categorizing, and evaluating potential risks with a level of comprehensiveness that often exceeds human performance. In a comparative experiment, GPT-4 outperformed human experts in construction project risk management tasks, particularly in risk identification and control, demonstrating its potential to enhance decision-making accuracy in complex planning environments. However, while AI-generated plans may be comprehensive, they sometimes lack the practicality and specificity found in human expertise, indicating that AI is best utilized as an augmentative tool alongside human judgment (NYQVIST; PELTOKORPI; SEPPÄNEN, 2024).

Complementing this, Zhang and Ge (2025) introduced the Off-Site Construction Risk Management Agent, a GPT-based model capable of analyzing qualitative interview data and structuring risk definitions with high precision. This type of tool allows planners to integrate qualitative and quantitative perspectives, building more comprehensive and data-driven risk registers (ZHANG; GE, 2025). Likewise, AI-powered conversational agents, such as the Dredging Project Risk Knowledge Chatbot, offer practical support for risk prevention planning and predictive analysis, enabling the identification and management of both anticipated and unexpected risks (CHOU; CHONG; LIU, 2024).

In summary, the incorporation of AI and LLMs into the planning phase transforms traditional project planning into a data-driven, adaptive, and collaborative process. By combining predictive analytics, risk reasoning, and natural language understanding, these technologies strengthen the analytical foundation of planning activities, improve alignment between project goals and constraints, and foster a more resilient approach to uncertainty management (PMI, 2023).

3.2.3 Execution, Monitoring, and Control Phases

The execution, monitoring, and control phases represent the operational core of project management, where plans are translated into tangible outcomes and continuously assessed against defined performance indicators. Project monitoring ensures a project is meeting milestones and deadlines. Large Language Models (LLMs) and Generative Artificial Intelligence (GenAI) are reshaping these stages by automating repetitive tasks, providing real-time analytical feedback, supporting complex decision-making, and enhancing adaptability in dynamic environments (PMI, 2024). These technologies act as intelligent assistants that augment human capabilities, enabling data-driven, responsive, and collaborative management practices throughout project execution (PMI, 2023).

LLMs excel in automating low-complexity, repetitive tasks that traditionally consume significant managerial and technical effort. In software engineering, multi-agent systems (MAS) powered by LLMs are being used to automate tasks such as code generation, code completion, documentation summarization, and backlog refinement, significantly reducing cognitive load and human intervention (CINKUSZ; CHUDZIAK; NIEWIADOMSKA - SZYNKIEWICZ, 2025; PMI, 2024). Similarly, in documentation and reporting, GenAI can automatically generate reports, meeting summaries, and stakeholder updates, streamlining communication and ensuring that information remains consistent across distributed teams (PMI SWEDEN, 2024).

In the Architecture, Engineering, and Construction (AEC) sector, GenAI automates repetitive processes within Building Information Modeling (BIM) workflows and Chatbots, accelerating the creation and updating of technical documentation and daily work reports and allowing professionals to dedicate more time to complex design and problem-solving (ONATAYO *et al*., 2024; CHO; PARK; LEE, 2023).

AI-assisted monitoring systems provide real-time insights into project performance, transforming traditional control mechanisms into continuous and adaptive feedback loops (PMI SWEDEN, 2024). Through automated data collection and analysis, GenAI tools can monitor key performance indicators (KPIs) such as schedule adherence, cost performance, and resource utilization, providing project managers with up-to-date dashboards and reports (PMI, 2024). In cost and budget control, AI tools analyze financial data to optimize resource allocation and detect deviations from budgeted expenditures early, allowing proactive adjustments (PMI, 2024; SHRESTHA; KO; LEE, 2025).

During the construction phase, text-to-text generative AI serves a pivotal function in tracking daily project performance and refining construction specifications. By continuously processing data from multiple sources, including sensors, progress reports, and communication records, this technology supports adherence to planned materials, procedures, and quality standards. Image-based AI models can automatically update architectural drawings using real-time photographs from construction sites, detecting design inconsistencies or deviations. Such real-time monitoring and adaptive optimization not only help ensure schedule compliance but also minimize material waste, lower energy consumption, and enhance resource efficiency, thereby promoting a more sustainable and data-driven construction process (ONATAYO *et al.*, 2024).

AI-driven quality assurance through automated testing significantly enhances the verification phase by using AI to analyze code, predict potential issues, and execute comprehensive test scenarios (PMI, 2024). Within LLM-powered Multi-Agent Systems, Quality Checker Agents are specialized for quality assurance, conducting code reviews, performing testing, and output validation to ensure deliverables meet predefined standards. Quality assurance is also enhanced through specialized “Quality Checker Agents” within multi-agent LLM frameworks which perform code reviews, execute test cases, and validate deliverables to ensure compliance with defined standards (CINKUSZ; CHUDZIAK; NIEWIADOMSKA -SZYNKIEWICZ, 2025).

AI also plays a central role in dynamic decision support, enabling project teams to adapt swiftly to changes and manage risks more effectively. Data-driven analysis allows AI to process vast quantities of information, identifying emerging trends, anomalies, and correlations that may not be evident through traditional monitoring (PMI, 2024; PMI, 2023). Cognitive agents powered by LLMs dynamically reassess priorities, adjust task sequencing, and reallocate resources in response to evolving project conditions, providing agility aligned with Agile and Lean project management principles (CINKUSZ; CHUDZIAK; NIEWIADOMSKA - SZYNKIEWICZ, 2025).

As mentioned in the previous section, AI significantly enhances identification, control, and mitigation processes for risk management, not only in the planning phase but also during the project execution (NYQVIST; PELTOKORPI; SEPPÄNEN, 2024; ZHANG; GE, 2025). Moreover, AI-based scenario simulations use predictive modeling to assess alternative outcomes and provide decision-makers with robust, data-informed strategies, allowing them to change routes effectively when a problem arrives (PMI, 2024; PMI, 2023).

AI also facilitates seamless information exchange and coordination, especially vital for distributed or complex multi-team environments. A fundamental element of project success lies in delivering accurate information to the appropriate stakeholders at the right moment. Achieving information synergy, where all decision-makers operate from a unified and consistent data foundation, is essential for alignment and effective collaboration. In the context of geographically distributed teams, rapid access to reliable knowledge sources enhances efficiency and reduces time spent searching for information. AI technologies are particularly well-suited to strengthen and augment project communication strategies by operating intelligent chatbots that provide on-demand information and by automating the real-time dissemination of project data across teams (PMI, 2024).

LLM-powered chatbots function as virtual project managers, providing continuous communication channels, answering queries, and summarizing key updates for distributed teams (CINKUSZ; CHUDZIAK; NIEWIADOMSKA -SZYNKIEWICZ, 2025). Alam *et al.*, 2025 provides an in-depth exploration of how AI chatbots are transforming communication and collaboration in project management, particularly within distributed and global teams. The AI-driven PDF Chatbot is designed to act as a virtual project manager capable of automating key management tasks, facilitating real-time communication, and ensuring uninterrupted project oversight. This innovation addresses a significant research gap by offering continuous operational support in situations where a human project manager may be unavailable, thereby redefining the dynamics of communication and collaboration in modern project management practices (ALAM *et al.*, 2025).

In construction and engineering projects, a chatbot has been developed and integrated into mobile communication platforms to assist field personnel in risk management and technical coordination. This system connects users to a central knowledge base, offering immediate, context-specific guidance during project execution (CHOU; CHONG; LIU, 2024).

3.2.4 Project Closing and Knowledge Management

The project closing phase marks the culmination of the project lifecycle, encompassing the formal completion of deliverables, performance assessment, and documentation of lessons learned. In this stage, Artificial Intelligence (AI) and Large Language Models (LLMs) have proven to be strategic allies, automating reporting processes, synthesizing project data, and facilitating institutional learning. Traditionally, the closing phase involves time-consuming activities such as compiling reports, reviewing project performance against planned objectives, and consolidating documentation for archiving. With the advent of Generative AI (GenAI), these processes can be performed automatically, allowing professionals to focus on reflective analysis and strategic insights rather than operational compilation (PMI, 2024).

GenAI-powered systems enable automated generation of final reports, executive summaries, and performance dashboards by aggregating and interpreting project data collected throughout the lifecycle. These tools can extract key milestones, summarize achievements, and generate comprehensive narratives that communicate project outcomes in an accessible and standardized format (PMI, 2023). In the AEC sector, text-to-text generative AI remains an important tool for ensuring continuity and efficiency. It assists in producing detailed as-built records and maintenance manuals, which are fundamental for the facility's long-term operation, upkeep, and management. Through the automated generation of precise and comprehensive documentation, this technology supports optimal building performance and helps preserve sustainability attributes throughout its entire lifecycle (ONATAYO *et al*., 2024).

Beyond documentation, AI contributes to systematic post-project evaluation by identifying lessons learned and supporting continuous improvement initiatives. By analyzing communications, reports, and stakeholder feedback, LLMs can detect patterns, correlations, and recurring issues that may not be immediately visible through manual review (PMI, 2023). Through semantic clustering, pattern detection and sentiment analysis, these systems categorize project insights into thematic areas such as planning efficiency, stakeholder engagement, and technical performance, offering a structured knowledge base for future initiatives (CHANG *et al.*, 2018; PMI, 2024). AI can also perform comparative analyses across multiple projects, enabling organizations to benchmark performance metrics and identify practices associated with success or failure. This analytical capability transforms post-project reviews into predictive knowledge resources that inform future strategic planning (SHRESTHA; KO; LEE, 2025).

LLMs have the capability to aggregate historical project information, particularly Lessons Learned (LL) records, and transform it into practical, data-driven insights. A notable proof-of-concept demonstrated the use of Generative AI (specifically ChatGPT) to merge multiple Excel files containing individual project LLs into a unified database. From this consolidated dataset, the system autonomously generated a set of ten targeted recommendations aimed at enhancing organizational processes and overall project performance (PMI SWEDEN, 2024). Chatbot-based systems have been effectively employed to centralize and disseminate expert insights, ensuring that technical and managerial knowledge remains available for future reference (CHOU; CHONG; LIU, 2024). These AI-driven knowledge repositories not only preserve documentation but also enable interactive access to lessons learned, allowing future project teams to query and retrieve context-specific guidance. This capability marks a transition from static archiving to dynamic, generative knowledge management, where AI continuously updates and refines organizational memory based on new inputs (PMI, 2024).

3.3 Challenges, Risks and Limitations of LLM in PM

The integration of Large Language Models (LLMs) into project management (PM) has introduced transformative capabilities, but also a complex set of challenges related to technical limitations, organizational adaptation, ethical issues, and cybersecurity vulnerabilities. These barriers reflect the tension between the promise of automation and augmentation offered by LLMs and the contextual constraints of real-world projects, where human expertise, governance, and ethical administration remain indispensable.

3.3.1 Factors Affecting LLM Performance

The efficacy of Large Language Models (LLMs) in project management tasks, particularly those requiring specialized knowledge or deep analytical capabilities, is constrained by inherent architectural limitations, dependence on high-quality data, and the necessity of precise human guidance. While these models have shown promise in automating analytical, linguistic, and decision-support functions across domains such as software engineering and construction management, their performance remains highly sensitive to contextual complexity and input quality (MAHBUB *et al.*, 2016; NYQVIST; PELTOKORPI; SEPPÄNEN, 2024; GAONA-CUEVAS; BUCHELI-GUERRERO; VERA-RIVERA, 2024).

Despite their advanced natural language capabilities, LLMs are limited by a constrained contextual window that restricts their ability to integrate and analyze information across long or multifaceted project documents. In the domain of software requirements analysis, GPT-4 exhibited difficulty in maintaining contextual coherence when cross-referencing requirements, leading to misinterpretations and a high incidence of false positives when detecting ambiguities and inconsistencies (MAHBUB *et al.*, 2016).

LLMs exhibit limitations in specialized domain knowledge and often lack the nuanced, human-like comprehension required for complex software or construction contexts. Consequently, they may misinterpret or overlook technical details that a human expert or analyst would normally clarify and resolve (MAHBUB *et al.*, 2016). In construction project risk management (CPRM), for instance, ChatGPT-4 demonstrated superior comprehensiveness compared to human experts but failed to produce practically implementable or contextually precise strategies; areas in which human domain expertise remains indispensable (NYQVIST; PELTOKORPI; SEPPÄNEN, 2024).

LLMs also struggle to perform causal reasoning or cross-validate complex dependencies across system elements. Mahbub *et al.* (2016) found that GPT-4 was unable to interpret state transitions and relational dependencies within software diagrams as effectively as human analysts. This suggests that current LLMs rely primarily on probabilistic associations rather than first-principles reasoning, which limits their reliability for engineering and design-related tasks that demand logical verification or multi-source reconciliation (SAHADEVAN *et al.*, 2025).

LLM performance also varies significantly depending on the task. In a comprehensive evaluation of GPT-4 applied to defect detection in software requirement documents, precision scores differed markedly across categories (0.61 for completeness, 0.43 for inconsistency, and 0.39 for ambiguity) (MAHBUB *et al.*, 2016). Such variability highlights the non-uniform nature of model generalization, where high performance in structured analytical tasks may coexist with poor results in ambiguous or highly technical ones.

Prompt engineering, the art of crafting precise and contextually rich instructions, plays a pivotal role in determining output accuracy. LLMs are highly sensitive to linguistic variations in input and even minor grammatical or syntactic changes can lead to substantially different results (CHANG *et al.*, 2018). The PMI emphasizes that generative AI tools must be “used with precision and tested iteratively”, as low-quality inputs yield unreliable or incoherent outputs. Organizations are increasingly recognizing that the quality of inputs is as crucial to AI performance as the underlying machine learning algorithms and datasets. As a result, many companies are investing in training employees to craft effective prompts, leading to the emergence of a new professional role within the AI ecosystem: the prompt engineer (PMI, 2024). Empirical evidence confirms that poorly structured prompts can mislead AI agents, reducing classification accuracy in tasks such as backlog refinement, risk identification and scheduling optimization (GAONA-CUEVAS; BUCHELI-GUERRERO; VERA-RIVERA, 2024; ZHANG; GE, 2025; WANG; WANG; CHU, 2025).

A persistent issue in LLM application is the phenomenon of hallucination, wherein the model fabricates information that appears plausible but is factually incorrect or inconsistent with project data. These hallucinations, categorized as factual (contradicting verified facts) or faithfulness errors (deviating from user instructions), arise because LLMs are designed to predict the most probable next token, even when lacking confidence or supporting evidence (PMI, 2024). Generative AI systems may produce misleading outputs or inaccurate predictions as a result of constrained training data or incomplete knowledge bases. Therefore, it is essential that stakeholders possess the capacity to verify the authenticity and reliability of AI-generated information (ONATAYO *et al.*, 2024).

When a model is exposed to overly extensive or overly generalized training data, its outputs may become distorted (PMI, 2024). Embedded biases within the data can propagate through the model, resulting in biased or unbalanced outcomes that may compromise design processes or decision-making (ONATAYO *et al.*, 2024). Large Language Models (LLMs), in particular, may unintentionally reproduce such biases or misinterpret subtle project requirements, as their knowledge is inherently derived from datasets that often mirror historical inequities or inaccuracies. These distortions can, in turn, influence how tasks are prioritized, interpreted, and communicated within project environments (CINKUSZ; CHUDZIAK; NIEWIADOMSKA -SZYNKIEWICZ, 2025).

3.3.2 Organizational and Integration Challenges

Implementing LLMs and GenAI into organizational project management workflows presents considerable practical, financial, and cultural barriers. The success of these technologies depends not only on algorithmic sophistication but also on the organization’s readiness to transform its structures, processes, and competencies to support AI-augmented decision-making (PMI, 2024; PMI, 2023).

Integrating GenAI tools such as ChatGPT into existing project management and design ecosystems is inherently complex. In the AEC industry, LLM-based applications, such as BIM-integrated chatbots or GPT-powered risk agents, require adaptation of legacy systems, data standardization, and often, new infrastructure to ensure interoperability (ONATAYO *et al.*, 2024). Existing information environments involve heterogeneous data formats, differing interface standards, and fragmented workflows across tools such as Building Information Modelling (BIM), scheduling software, and enterprise databases. These inconsistencies make it difficult to embed LLMs and Deep Learning (DL) frameworks into the operational lifecycle of construction projects (LI *et al.*, 2024).

The financial implications are equally significant. According to PMI, integrating AI into PM processes requires not only investment in computational resources and data storage but also in staff training and change management programs. Without adequate infrastructure, organizations face inefficiencies in model integration and inconsistent outputs that undermine stakeholder confidence (PMI SWEDEN, 2024; PMI, 2024).

Even when technical and financial conditions are favorable, organizational resistance often poses a barrier to adoption. The implementation of AI systems typically demands substantial modification of established workflows, decision hierarchies, and communication routines; factors that can trigger skepticism or fear of displacement among employees (PMI, 2024b; AL NAQBI; BAHROUN; AHMED, 2024; ZIRAR *et al*., 2023). Studies indicate that cultural inertia and limited trust in AI-generated recommendations significantly delay integration, particularly in industries with strong traditions of experiential knowledge, such as engineering and construction (NYQVIST; PELTOKORPI; SEPPÄNEN, 2024).

In addition, the effective adoption of generative AI requires multidisciplinary competencies that combine project management, domain expertise, and data science (ONATAYO *et al*., 2024). However, the current workforce exhibits significant skill gaps, particularly in "AI literacy" and prompt engineering (LI *et al*., 2024; WANG; WANG; CHU, 2025). PMI research indicates that only about one-fifth of project professionals report having extensive experience with AI tools or techniques (PMI, 2024b).

To mitigate this, organizations must invest in training and reskilling programs that enable professionals to interpret, validate, and refine AI outputs effectively (PMI SWEDEN, 2024). Emerging roles, such as "AI project facilitator" or "prompt engineer", are becoming increasingly critical for maintaining the integrity of GenAI-assisted decision-making (PMI, 2024). Without such human oversight, the benefits of automation risk being offset by model misapplication or misuse.

3.3.3 Ethical and Cybersecurity Risks

The deployment of Large Language Models (LLMs) introduces serious ethical and security vulnerabilities, particularly in organizational environments where sensitive project and financial data are managed. As these models become embedded into project management workflows, whether in design generation, scheduling, or risk analysis, their ability to autonomously process, generate, and disseminate information raises complex issues surrounding fairness, transparency, accountability, and data protection (PMI, 2024; PMI, 2023; ALAM *et al*., 2025).

AI systems are inherently dependent on the data used to train them, and this dependency renders them susceptible to the biases embedded in historical datasets. When training data contain skewed or discriminatory patterns, LLMs may reproduce or amplify these biases in project-related predictions and decisions. This can manifest as unfair resource allocation, discriminatory prioritization of projects, or exclusionary forecasting models (PMI SWEDEN, 2024). Mitigating bias in AI models is a fundamental challenge that requires ongoing oversight and evaluation. Continuous monitoring of model outputs is essential to detect and correct biases originating from unbalanced training datasets or algorithmic deficiencies. The adoption of fairness-aware machine learning approaches, along with the inclusion of diverse and representative data sources, constitutes a key strategy for minimizing these distortions. Additionally, cultivating an organizational culture grounded in ethical AI principles, through targeted training and awareness initiatives, reinforces the responsible, transparent, and trustworthy implementation of AI technologies across business and project contexts (CINKUSZ; CHUDZIAK; NIEWIADOMSKA -SZYNKIEWICZ, 2025).

Most generative AI systems operate as “black boxes”, offering limited visibility into their decision-making processes (ONATAYO *et al.*, 2024). Their outputs are often based on probabilistic token predictions rather than traceable causal reasoning, which impedes users’ ability to understand or validate their internal logic (SAHADEVAN *et al.*, 2025). This lack of explainability presents a major obstacle to professional accountability, especially in engineering and AEC contexts where regulatory compliance and safety validation are essential (NYQVIST; PELTOKORPI; SEPPÄNEN, 2024).

AI-assisted decisions may conflict with ethical norms or organizational policies due to ambiguous responsibility boundaries (PMI SWEDEN, 2024). It remains unclear who holds accountability when AI-generated recommendations lead to project errors or failures, whether it is the developer, the project manager, or the organization implementing the system (PMI, 2024). This uncertainty is compounded by the risk of misinterpreting AI-generated insights, especially when outputs are taken at face value without expert verification. The PMI Navigating AI Report (2024) emphasizes that AI adoption must be accompanied by transparent governance frameworks to ensure that project managers and decision-makers can interpret AI-derived insights and justify them to stakeholders.

A further ethical concern is the potential misuse of LLMs for generating misleading or fabricated information. When malicious actors intentionally feed biased or false data into AI systems, these models can produce plausible yet incorrect narratives, fostering disinformation (PMI, 2024). LLMs’ capability to generate persuasive natural language at scale raises the risk of automated misinformation campaigns or the manipulation of stakeholder perception through falsified project documentation or progress reports. Such risks necessitate robust verification protocols and human oversight to prevent the dissemination of fabricated or unethical outputs (PMI SWEDEN, 2024).

LLMs frequently process sensitive corporate and project data, such as contractual terms, personal details, proprietary designs, and financial metrics, which exposes organizations to confidentiality breaches (ONATAYO *et al*., 2024). Publicly hosted models like ChatGPT or Bard (Gemini) do not guarantee that user-provided inputs remain private, as queries may be stored and reused for further model training (PMI, 2024). In project management contexts, this can compromise intellectual property rights and contractual confidentiality.

If not properly governed, data collection processes may inadvertently capture sensitive or personally identifiable information (PII). For example, an AI system designed to analyze customer feedback could unintentionally gather names, addresses, or other private details from reviews or social media posts. Without adequate anonymization or encryption during data storage, such information becomes vulnerable to cyberattacks, increasing the risk of data breaches. Unauthorized access to this data can lead to serious privacy violations, harming affected individuals and potentially damaging the organization's credibility, trustworthiness, and overall reputation (PMI, 2024).

Considering that OpenAI has previously reported a data breach, concerns regarding data privacy and security have become more pronounced. ChatGPT currently lacks comprehensive mechanisms to ensure full compliance with data protection frameworks such as the General Data Protection Regulation (GDPR) (CASTELBLANCO; CRUZ-CASTRO; YANG, 2024). However, the Enterprise version, which includes enhanced privacy controls, data encryption, and stronger governance mechanisms, demonstrates OpenAI's ongoing efforts to mitigate these risks and respond to prior criticisms by strengthening the platform's security and data protection standards (SONKOR; GARCIA DE SOTO, 2024).

In summary, while LLMs offer unparalleled potential to augment project decision-making and automate complex analytical tasks, their ethical and cybersecurity implications necessitate robust governance structures. Ensuring transparency, data protection, and responsible AI use is essential for maintaining stakeholder trust and safeguarding organizational integrity in AI-augmented project management.

3.4 Future Trajectories

The integration of Artificial Intelligence (AI) and Large Language Models (LLMs) represents a transformative juncture for software engineering and project management, marking the advent of what the PMI calls the “Exponential Age”: a period of exponential technological progress that is reshaping organizational structures, roles, and competencies (PMI, 2024).

Figure 5 below demonstrates that several leading project management platforms, such as Asana, ClickUp, Monday, Jira, and Microsoft Project, already integrate AI features into specific functions like writing assistance, task management, resource planning, forecasting, and cost management. This growing presence of AI within traditional project management tools shows that automation and intelligent support are no longer futuristic concepts but current realities in the field. However, the extent of AI adoption still varies across platforms: while some tools focus on automating scheduling and forecasting, others leverage natural language processing for communication and documentation support (PMI, 2024). In the near future, it is expected that AI integration will become broader and more sophisticated, enabling project managers to make data-driven decisions faster, predict risks with greater accuracy, and reduce administrative workload.

Figure 5 - Organizational and PM tools with an AI component

Product	Writing Assistance	Task Management	Forecasting	Resource Planning	Cost Management
Asana	✓	✓			
ClickUp	✓	✓		✓	
Coda	✓	✓			
Forecast		✓	✓	✓	✓
Grammarly	✓				
HubSpot	✓	✓			
Jira		✓		✓	
Kantata		✓	✓	✓	✓
Microsoft Project	✓	✓			
Monday	✓				
Notion	✓				
ProofHub		✓		✓	
Sembly	✓				
Scoro		✓	✓	✓	✓
Taskade		✓			
Teamwork		✓	✓	✓	
Wrike	✓	✓			
Writer	✓				
Zapier		✓			

Source: PMI, 2024.

3.4.1 Changes in the perspective about AI and the role of the project manager

The prevailing perspective on AI in project management has shifted from viewing it as a replacement for human labor to perceiving it as a collaborative and augmentative tool. Instead of supplanting human decision-making, AI systems, particularly Generative AI (GenAI), serve to enhance analytical capabilities, automate repetitive operations, and amplify human creativity (PMI, 2024). As artificial intelligence increasingly automates routine and repetitive tasks, the nature of project management roles is expected to evolve. Certain manual or administrative responsibilities may be replaced or augmented by AI-driven systems, potentially reshaping job functions and skill requirements. Consequently, project managers will need to adapt by focusing on higher-value activities such as strategic decision-making, stakeholder engagement, and the ethical oversight of AI-enabled processes (PMI SWEDEN, 2024).

The notion of Augmented Intelligence emphasizes human–machine collaboration rather than autonomy, positioning AI as a co-pilot in decision-making processes (PMI, 2024). As routine work becomes increasingly automated, human capabilities become the primary source of competitive differentiation. PMI categorizes these essential capabilities as “Power Skills”, encompassing strategic thinking, problem-solving, collaborative leadership, and effective communication (PMI, 2023). AI augments these traits by providing predictive insights, coordinating communication, and managing real-time data, yet ethical reasoning, empathy, and accountability remain inherently human (PMI, 2024).

To thrive in this environment, project managers must cultivate a new set of competencies (non-exhaustive):

a) AI Fluency: A foundational understanding of AI principles and functionalities must be embedded in the project manager’s professional identity (ONATAYO *et al.*, 2024);
b) Continuous Learning: The AI Essentials for Project Professionals report underscores that technological acceleration creates a “perpetual learning cycle” requiring constant skill renewal and adaptation (PMI SWEDEN, 2024; ZIRAR *et al*., 2023).
c) Data Literacy and Management: Proficiency in data curation, preprocessing, and quality control is crucial, as AI effectiveness depends on well-structured and representative datasets (PMI, 2023)
d) Prompt Engineering: As highlighted before, refining the interaction between human prompts and AI responses enhances reliability and reduces model hallucinations (PMI, 2024; NYQVIST; PELTOKORPI; SEPPÄNEN, 2024)

Through these evolving skills, the project manager transitions from an operational coordinator to a strategic integrator of human–AI collaboration, driving both innovation and governance across project ecosystems.

3.5 Literature Summary and future directions

In conclusion, it is possible to understand that Artificial Intelligence, specially Large Language Models, are being applied in many topics related to Project Management. The main applications identified can be summarized in Table 3 below, indicating the references according to Appendix A.

Table 3 - Summarization of AI applications in PM

AI Application	Reference	Count
Prioritization	[1] [4] [5] [6]	6
Resource allocation	[1] [4] [6] [7] [8] [9] [10] [11]	8
Scheduling	[1] [2] [4] [7] [8] [9] [11] [12] [13]	9
Risk identification and management	[1] [2] [4] [6] [10] [11] [14] [15] [16]	9
Cost management	[1] [2] [3] [9] [11] [17]	6
Decision-making	[1] [4] [6] [9] [10] [14] [16] [18] [19]	9
Reporting and documentation	[1] [2] [4] [9] [10] [12] [20]	7
Monitoring and Control	[1] [8] [9] [10] [20]	5
Communication and Collaboration	[1] [2] [4] [6] [10] [16] [20]	7

Source: Created by the author.

Across the nine categories presented, scheduling, risk identification and management, and decision-making emerge as the most frequently cited applications, each referenced by nine studies, indicating their centrality in current AI-driven project practices. Resource allocation and communication and collaboration follow closely, suggesting that AI is increasingly leveraged to enhance coordination and optimize the use of project resources. Applications related to reporting and documentation, cost management, and monitoring and control also appear consistently, reflecting the growing role of AI in automating operational tasks and strengthening governance mechanisms. Taken together, the distribution of references demonstrates that AI is not confined to a single dimension of project work; rather, it permeates both strategic and operational processes, supporting decision quality, efficiency, and information management throughout the project lifecycle.

According to the PMI Shaping the Future of Project Management with AI report, AI is already influencing project execution globally, with 82% of senior leaders affirming that AI will have a significant impact on project management practices within the next five years (PMI, 2023).

The convergence of cognitive agents, Large Language Models (LLMs), and Multi-Agent Systems (MAS) within Agile development environments presents considerable potential for future research. A central focus for advancing this field lies in examining the scalability and interoperability of the LLM ecosystem across software projects of varying sizes and complexities. Furthermore, enhancing models of human–AI collaboration represents another critical direction for inquiry. The development of advanced interfaces and mechanisms that foster mutual learning between human developers and AI agents could significantly improve team cohesion and productivity. Refining MAS architectures to align more closely with Agile principles may also enable LLMs to emulate and facilitate human-like interactions within software teams. Embedding predictive analytics within these systems could further support proactive project management by identifying potential delays and enabling early corrective actions (CINKUSZ; CHUDZIAK; NIEWIADOMSKA -SZYNKIEWICZ, 2025).

Research should also focus on applying AI beyond theoretical settings by redesigning real-world project management processes to fully exploit LLM capabilities. This includes developing new process models and governance protocols that balance innovation, human oversight, and accountability. (PMI SWEDEN, 2024; NYQVIST; PELTOKORPI; SEPPÄNEN, 2024).

The ethical dimension of AI integration remains a critical area for investigation. Al Naqbi, Bahroun and Ahmed (2024) emphasize the need to ensure fairness, privacy, and transparency in AI implementation. The PMI echoes this by recommending bias mitigation frameworks, continuous monitoring of model outputs, and transparent audit trails. Security concerns must also be addressed through robust encryption, data anonymization, and access control systems (PMI, 2020).

Additionally, evaluation frameworks must evolve to capture AI resource's multidimensional performance across contexts. Scenario-oriented assessment methods and domain-specific taxonomies are required to measure AI efficacy. The central argument is that evaluation must be regarded as a fundamental discipline for ensuring the effectiveness and reliability of Large Language Models (LLMs) and other AI systems. Current evaluation frameworks remain insufficient to comprehensively assess the models' true capabilities, limitations, and contextual adaptability. This gap underscores significant challenges while simultaneously opening new avenues for research dedicated to developing more rigorous, multidimensional, and standardized evaluation methodologies for LLM performance assessment (NI *et al.*, 2025).

Collectively, these directions indicate a profound paradigm shift in AI research within project management: one that moves decisively beyond narrow notions of automation toward the development of responsible, explainable, and domain-adaptive intelligence. This emerging trajectory emphasizes not only technical advancement but also the embedding of ethical safeguards, transparency mechanisms, and contextual sensitivity into AI-enabled project environments. As organizations increasingly rely on AI to support complex decision-making, the research agenda progressively converges on designing systems capable of justifying their outputs, learning from domain-specific nuances, and adapting to evolving organizational processes. In this sense, future innovation depends on cultivating AI ecosystems that enhance human judgement rather than replace it, ensuring that project management practices remain accountable, trustworthy, and deeply aligned with the sociotechnical realities in which they operate.

4 CASE STUDIES

Drawing on the interview data, a qualitative analysis was conducted, using the NVivo software, to examine how each company understands and employs artificial intelligence in project management. Accordingly, the results are organized into some sections: an overview of each interviewee's account, the AI applications, benefits, and challenges identified, the relationships emerging across codes, leadership and governance aspects and, finally, a discussion of future perspectives.

4.1 AI Understanding and Perception

Across the five participating companies, interview data reveal a convergent yet heterogeneous understanding of artificial intelligence (AI) and its role in project management. Although all organizations demonstrate awareness of AI's strategic relevance, their conceptualizations range from viewing AI as an automation tool to recognizing it as a transformative analytical capability.

4.1.1 Company 1

C01 employee conceptualizes AI nowadays mainly as an assistant, particularly for "less noble" tasks such as document scanning and detailed searches, and also to provide alternative approaches.

> Our understanding is that it is supposed to provide the equivalent to an assistant's service. In fact, what we use the most is really to do what we call 'less noble' tasks, like performing a more careful search within some long documents, for example. There are some things you can't really escape, like some deeper analysis. Before, you had to do it by yourself, it was just you and the paper, you and the computer screen, but now, at least, you have something to guide you, that can see something you weren't noticing. (C01, author's translation)

There is also a growing expectation of automation and potential job substitution. The interviewee emphasizes a structural shift:

> Maybe, there could be a person to perform a role and they won't be needed anymore. But, it's still a support for the main functions. We know the intention is for AI to become more autonomous, to replace some functions in the future. [...] It will replace hundreds with dozens, thousands with hundreds, it won't be linear; a team of ten could be replaced by two. (C01, author's translation)

4.1.2 Company 2

The interviewee from C02 demonstrates a conceptual grasp of AI that goes beyond generative models, since it has a data scientist background, however, recognizes that while this conceptual distinction is understood, that is not what is the day-today of the team members. For most people in the company, AI is a supporting tool, to facilitate their daily tasks.

> I have a more conceptual understanding regarding artificial intelligence, but that is not our team's day-to-day focus. [...] Artificial intelligence is something much bigger than generative AI [...] But looking at the team's day-to-day, today we have AI here much more as a support tool for our user. (C02, author's translation)

The perception of AI in C02 is strongly aligned with augmentation rather than substitution. The respondent explicitly rejects the idea of replacement at this stage, framing AI as a tool for improving usability, supporting data preparation, and reducing operational friction. Automation is acknowledged as a long-term possibility but dependent on significant backend integration.

> The organization's goal is not to replace people, but rather to help them [...] Partial replacement is a possible future, but it requires automation behind it, which is not done by the LLM alone. So, the team needs to continue existing to work on these automations and allow things to connect. (C02, author's translation)

4.1.3 Company 3

C03 presents the most structured conceptualization of AI, linking it explicitly to computational replication of human knowledge. In practice, AI is framed as part of a broader analytic toolkit, not only GenAI, that is the most popular concept nowadays. The interviewee emphasizes that AI is not about creating autonomous agents, but about solving business problems with intelligence-driven techniques.

> I could give an academic definition, which is a science that studies how computers can replicate human knowledge. But in practice, I believe we understand it as a practice in projects to generate some business value. [...] We are not creating a robot that is going to take over the planet or anything like that. On the contrary, we are using AI oriented toward a business problem that will be solved with a broad statistical and mathematical intelligence capability. (C03, author's translation)

Perception is strongly tied to responsibility and process integrity. C03 rejects the notion of AI as a substitute for human judgment and emphasizes the need for user supervision and critical review.

> The way the company functions as a consultancy remains the same. You just have a tool to do things faster, not to skip steps. I believe looking at it this way makes it safer [...] we never communicated it as 'AI is replacing a step in your work,' but rather as 'it is accelerating the process and you have the responsibility for the outcome'. (C03, author's translation)

They also adopt a long-term perspective, viewing AI as a technology that will become omnipresent and largely invisible, much like the internet. While it is heavily discussed today, it is expected to integrate naturally into daily life.

> This topic of artificial intelligence will soon stop being popular because it will become so commonplace; it will be something that will be very much in our daily lives in the

> coming years, just as nowadays we don't talk much about the internet as being a big deal. I really see it going the same way. [...] for me, artificial intelligence, deviating from the academic definition, will become the main day-to-day tool for everyone who has some connection with it, just like a computer, a cell phone, or the internet. (C03, author's translation)

4.1.4 Company 4

C04 demonstrates a more narrative and experiential understanding of AI. Early perceptions were shaped by science-fiction imagery but have evolved toward a data-driven notion of AI as consolidating data and translating it into meaningful analytical insight.

> In the beginning, when this artificial intelligence thing came up, we related it to the books, videos, and films about robotics, something very innovative [...] And today I have a very clear concept of what artificial intelligence is [...] it really is taking all the data, the data compilation, and turning it into useful things, things that can help people gain insights [...] artificial intelligence is about expanding knowledge to everyone. (C04, author's translation)

The company perceives AI as a hybrid of substitution and support, depending on the task. For instance, intelligent cameras reduce the need for human monitors, while documentation tasks remain mostly supportive:

> I think it's a mix of both, depending on what you are going to do and apply, I think it can be a combination of the two. [...] Our smart cameras that do monitoring, if they didn't exist, some people would need to be there monitoring [...] but at the same time for day-to-day things, like documentation, it's also a lot of support. (C04, author's translation)

A key aspect of the interviewee's perception is critical vigilance. He stresses the importance of not trusting AI blindly. Thus, AI is perceived simultaneously as a knowledge-expanding instrument and a potential source of misinformation, requiring human evaluation and contextual expertise.

> I talk a lot with my team. We cannot believe it 100%; we really have to seek to understand if it is true [...] I think nothing can replace our life knowledge, career experience, and study. So, you can update yourself on a standard, you can update yourself on a subject, but you really cannot blindly trust it. You need to have a second source for research. (C04, author's translation)

4.1.5 Company 5

C05, as the newest company in the market and a startup, presents the most innovative perspective on AI, characterized by fewer restrictions and a greater willingness to experiment with applications. C05 also recognizes AI as a rapidly evolving area of knowledge, facilitated by innovations such as attention mechanisms.

> It is an area of knowledge whose adoption has increased lately, with some recent innovations, especially concerning the attention matrix [...] which has made things more accessible and smarter. (C05, author's translation)

The interviewee expresses the strongest belief in the inevitability of AI-driven substitution. However, this substitution is still envisioned through the lens of augmentation: the initial phase of adoption positions AI as a support tool, offering the type of support traditionally provided by junior professionals. This creates a dual perception: AI will inevitably automate certain tasks, but its entry point is as a cognitive partner designed to enhance thinking and accelerate ideation.

> I think it is inevitable that AI will replace human functions, but the first adoption will be as a supporting tool. I think it replaces human functions because some professions also involve a lot of data analysis, pattern analysis, some pre-established process, or even intellectual support itself, for example, a more senior person needs to talk to a more junior person to develop an idea, and artificial intelligence fulfills that role today. (C05, author's translation)

4.2 Company's profile

As demonstrated in the previous chapter, the companies vary considerably in terms of years of operation and organizational size, factors that can influence their patterns of AI adoption. Table 4 synthesizes the extent and nature of AI use across the five cases.

Table 4 - Overview of LLM adoption across companies

Company ID	Spread of LLM use	Frequency of use*	Models use	Own platform	AI Corporate License
C01	2023	3-4 days/week	ChatGPT, Gemini, Notebook LM	No	None
C02	2024	2-3 days/week	ChatGPT, Gemini, Claude, Copilot	Yes	Gemini Pro
C03	2023	Everyday	ChatGPT, Gemini	Yes	Gemini Pro
C04	2024	Everyday	ChatGPT	Yes	ChatGPT Plus
C05	2024	Everyday	ChatGPT, Gemini, Claude, Copilot	No	None

*Interviewee's frequency, not necessarily company's representation

Source: Created by the author.

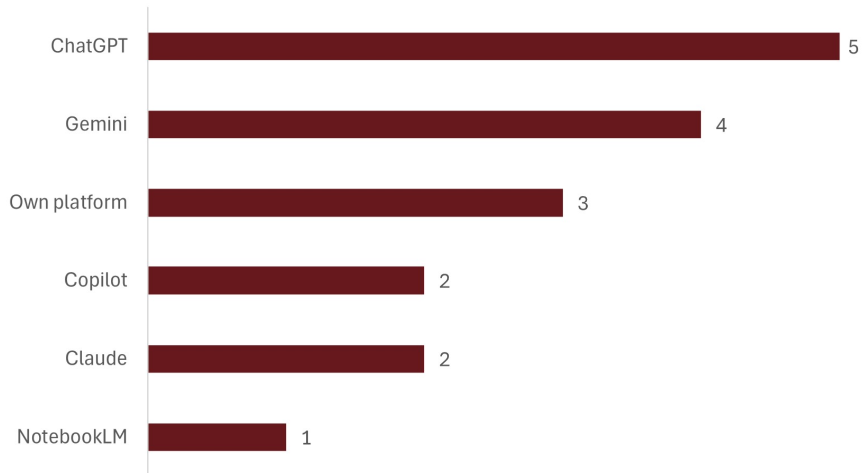
Table 4 reveals variations in the timing of adoption, frequency of use, and level of institutionalization of AI tools. C01 and C03 were early adopters, both introducing GenAI in 2023, whereas C02, C04, and C05 began using these tools only in 2024. It is important to note that I02 emphasized that conversations about AI had already been occurring within the leadership team prior to 2024. However, it was only in 2024 that the company began strongly incentivizing AI use, and the topic became one of the most frequently discussed internally.

C03 also presented evidence that their very first client engagement involved a project that already incorporated a form of AI, even if the term was not used explicitly at that time. Furthermore, in 2021 the company created a dedicated division focused exclusively on AI-related initiatives. By 2023, C03 had significantly increased its investment in AI, began publicly commercializing its AI expertise, and encouraged all employees to integrate AI into their daily work practices. Another important clarification is that C04 began using AI in its Madrid operations in 2022, however, leadership-driven guidance and investment in AI tools in the Brazilian branch only commenced in 2024.

Frequency of use also differs meaningfully across cases. I01 and I02 employ LLMs on a regular but non-daily basis, 3-4 days and 2-3 days per week, respectively, indicative of a more situational or task-dependent adoption. In contrast, I03, I04, and I05 report daily use, signalling a more embedded and operationalized integration of GenAI into routine workflows. This pattern aligns with the interview findings that these companies, particularly C03 and C04, have internal guidelines, standardized practices, or stronger managerial incentives that promote continuous use.

The table also highlights the diversity of commercial AI models adopted across the cases. Figure 6 presents the number of companies that reported using each tool during the interviews. All five companies rely on ChatGPT to some extent, even when it is not the organization's officially endorsed tool. The term "ChatGPT" appeared 48 times across all interviews, underscoring the centrality of OpenAI's model in current professional practice. Google's Gemini is used by four companies and was referenced 28 times. Some companies complement these two dominant models with additional tools, such as Claude and Copilot, primarily for coding-related tasks, and Notebook LM, which is used for document analysis and summarization.

Figure 6 - Number of companies using each AI tool



Source: Created by the author.

C03's perspective is that the choice of AI models is driven more by individual preference than by substantial differences in application. According to the interviewee, ChatGPT and Gemini offer largely comparable functionalities, with only marginal differences in specific features. Users tend to continue using the tool with which they first became familiar, as their initial exposure shaped their foundational understanding of how AI works.

> There is a personal matter of habit where, for example, even though you objectively have iPhones and Galaxys in the world, people fight, saying one is better than the other simply due to personal preference, and this will happen to everything. [...] What I see as the reason people prefer ChatGPT or Gemini? It's something that came out earlier. So, people created a concept based on those tools, which makes them a very easy first choice. (C03, author's translation)

Regarding the preference for internal versus commercial platforms, C03 emphasized the disparity in lead time: internal platforms tend to replicate commercial models, resulting in delayed access to newly released functionalities. Another relevant distinction concerns the degree of specialization of each tool. Some models are perceived as more effective for general, routine tasks, whereas others are considered better suited for specialized or domain-specific activities.

> They are the companies that are furthest ahead. So, if something new is launched, it will come out on ChatGPT and Gemini first, and it will take us as a company two months to implement. So there is a difference in lead time for things to happen. If something really cool comes up, people will tend to quickly migrate to that solution, and eventually we will catch-up. (C03, author's translation)

An important structural distinction concerns the ownership of internal AI platforms. C02, C03, and C04 have developed proprietary platforms or internal interfaces to facilitate AI use, a feature often associated with higher digital maturity and stronger commitments to long-term AI integration. In contrast, C01 and C05 rely solely on external tools, which may reduce development costs but can limit customization and data governance capabilities.

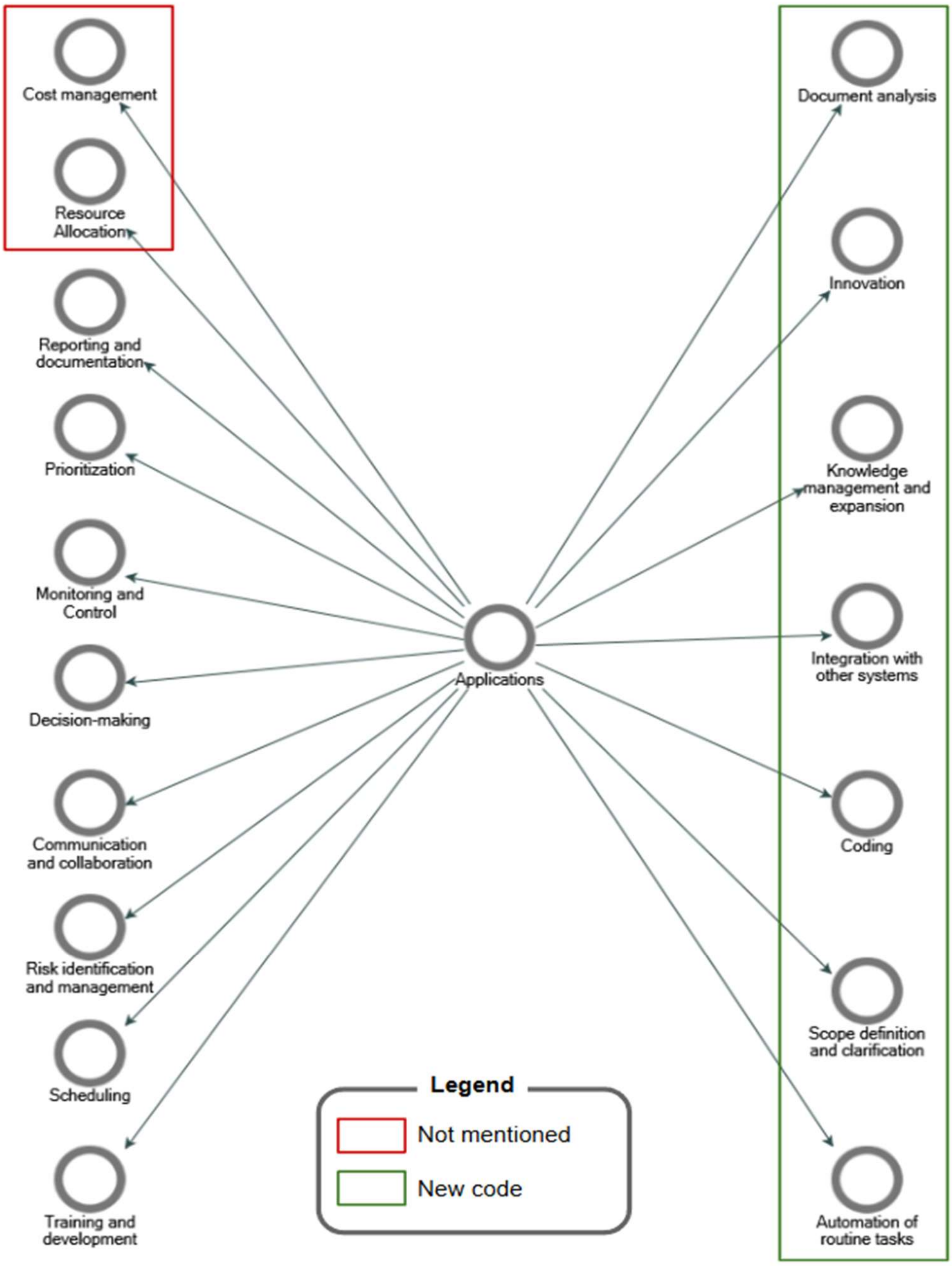
Finally, the table highlights differences in corporate licensing. Three companies, C02, C03, and C04, have invested in paid corporate AI licenses (Gemini Pro or ChatGPT Plus), the same ones that developed their own platforms. This signals an institutional decision to formalize and secure AI usage, likely driven by concerns related to data privacy, functionality requirements, and service reliability. C01 and C05, that operate without corporate licenses, tend to adopt a more exploratory, low-investment approach, which may be associated with the smaller workforce of these two companies, reducing the need for strict managerial oversight.

Collectively, the information in Table 4 demonstrates that AI adoption among the five companies is heterogeneous and shaped by organizational maturity, strategic priorities, and resource availability. The presence of internal platforms and paid licenses appears to correlate with more intensive and structured usage patterns, whereas companies without these components tend to use AI in a more unstructured manner, which represents a lower maturity level.

4.3 Applications

Figure 7 presents the hierarchical coding structure developed for the category Applications, synthesizing all references to how AI is being used across the five case companies. The diagram illustrates the parent node Applications at the top, followed by the full set of subcodes generated through open and axial coding. Overall, the figure reflects a diverse and evolving landscape of AI applications.

Figure 7 - Applications Coding



Source: Created by the author using NVivo.

Each circle represents an application domain identified in the interviews. Codes outlined in green correspond to new codes that emerged inductively during the analysis; applications not initially anticipated in the analytical framework but consistently observed in the empirical material. These include, for example, automation of routine tasks, coding, scope definition and clarification, integration with other systems, knowledge management and expansion, innovation, and document analysis. Their emergence indicates that interviewees perceive AI as increasingly embedded in broader knowledge processes, system interoperability, and exploratory activities.

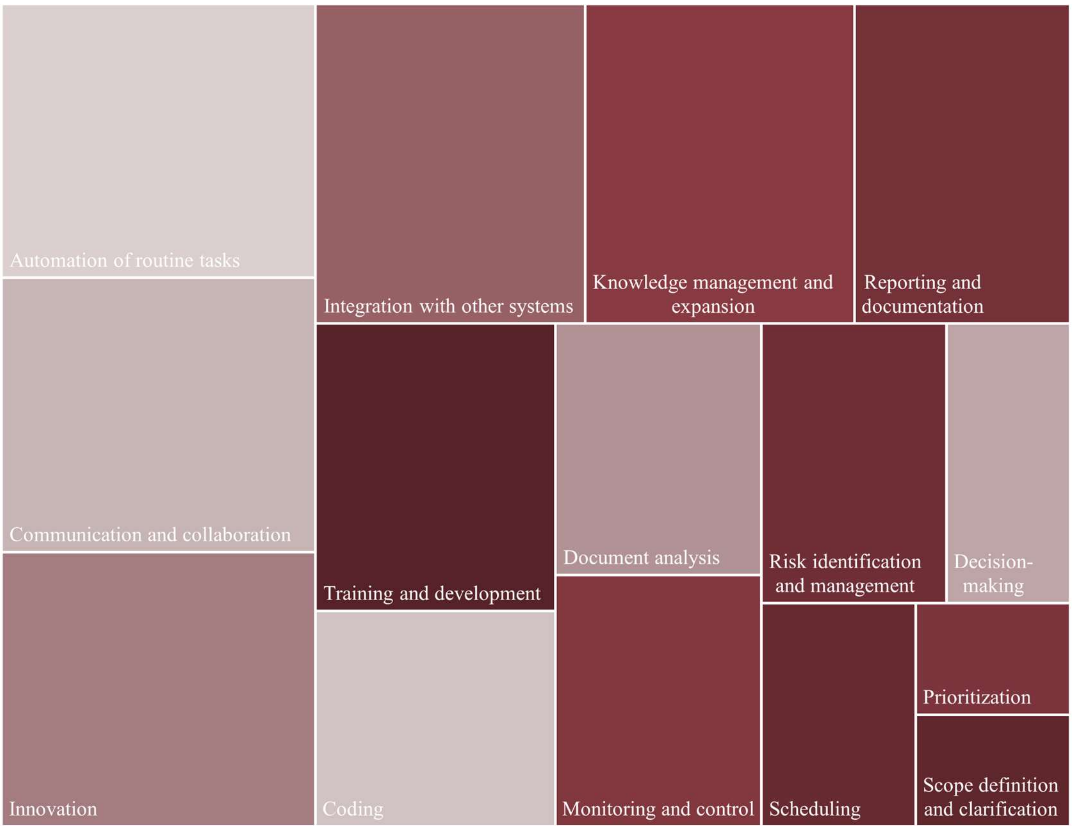
Regarding knowledge, all companies mentioned the use of LLMs as mechanisms to expand knowledge, learn new topics, and access previously developed materials in a fast and practical manner, including requesting that the model use a specific language or source:

> I think the first point is extremely relevant, which is people development. You can use it to ask questions, clarify doubts, look up internal company content or material from university classes. Learning is by far the area where we use it the most. You access it, ask a question, and that is learning in action. (C03, author's translation)

In contrast, the codes highlighted in red represent application areas that were part of the initial analytical structure but were not mentioned by any interviewee, namely, cost management and resource allocation. Their absence suggests that, although the literature associates AI with optimization and resource planning, such uses are not yet prevalent or salient in the daily practices of the studied companies.

The treemap in Figure 8 illustrates the distribution of AI application areas mentioned across the five companies. The visualization highlights substantial variation in the prominence of each application, revealing which uses of AI are more consolidated in organizational practice and which remain marginal or emerging.

Figure 8 - Frequency-Based Visualization of AI Applications



Source: Created by the author.

The most frequently mentioned applications, automation of routine tasks, communication and collaboration, integration with other systems, knowledge management and expansion, and innovation, were cited by all five companies. Their prominence in the treemap, represented by larger blocks, indicates that these domains constitute the core of AI integration in project environments. These applications align with the broader academic literature that positions AI as a tool for enhancing efficiency, supporting real-time information sharing, and enabling more advanced knowledge processing (PMI, 2024). Their universal mention also suggests that such uses are less dependent on organizational size or maturity and instead reflect common opportunities perceived across industries.

A significant share of the interviewees emphasized the use of AI to record and transcribe meetings, draft emails, messages, and announcements, thereby facilitating communication among individuals:

> I personally use it a lot for corporate communication. Whenever I need to write an announcement to launch a new feature in my product, I rely on AI to help me craft those messages. (C02, author's translation)

In addition, all companies reported already using certain AI integrations with project softwares and Google tools, though in a punctual and highly specific manner:

> What we have in terms of integration is with some tools, such as those from NVIDIA. One example is a 3D building visualization tool, and we integrate OpenAI with that tool so that you can navigate it using voice commands. (C01, author's translation)

Training and development and reporting and documentation were each mentioned by four companies, indicating a relatively higher degree of consolidation in these areas. In contrast, document analysis, monitoring and control, and risk identification and management were mentioned by three companies, reflecting a slightly more selective adoption. All five of these applications appear as medium-sized rectangles in the treemap, signaling that they are present in the majority of organizations, though not universally adopted. Their lower frequency compared to the core applications suggests that they may require more robust infrastructure, data governance practices, or specific internal competencies, which could account for the variability in uptake. Moreover, these domains often involve more structured processes or rely on domain-specific knowledge, which may limit their diffusion among organizations still in earlier stages of AI integration.

One company mentioned using AI to generate daily construction reports, which were previously onerous to produce and often contained grammatical errors; this issue was partially mitigated through the adoption of AI tools:

> When the team goes out to the field to carry out the project, we need them to produce DCRs, the daily construction reports. Many times, the reports would come in with very little information or with some mistakes. So we tell them to just type in the notes as they are and see what it generates, then they review it. [...] They review it and refine the texts. Something that used to be tedious becomes much more streamlined. (C01, author's translation)

Other domains, such as decision-making and scheduling, were mentioned by two companies. Their smaller blocks in the treemap reflect a more selective adoption pattern. These activities are typically associated with more complex, high-stakes processes that require higher reliability, model interpretability, and managerial oversight. The lower frequency is consistent with recurring concerns about trust, accuracy, and accountability in automated or AI-supported decision processes observed in the interviews.

Finally, prioritization and scope definition and clarification were mentioned by only one company each, while cost management and resource allocation were not mentioned at all. This absence is analytically relevant: despite being domains often emphasized in the literature as prime areas for AI optimization (e.g., scheduling algorithms, cost estimation models), they are not yet reflected in the everyday practices of the companies studied. This gap may indicate that Brazilian project environments remain in the early stages of leveraging AI for more advanced analytical and optimization functions, focusing instead on applications that support content generation, communication, and general productivity enhancement.

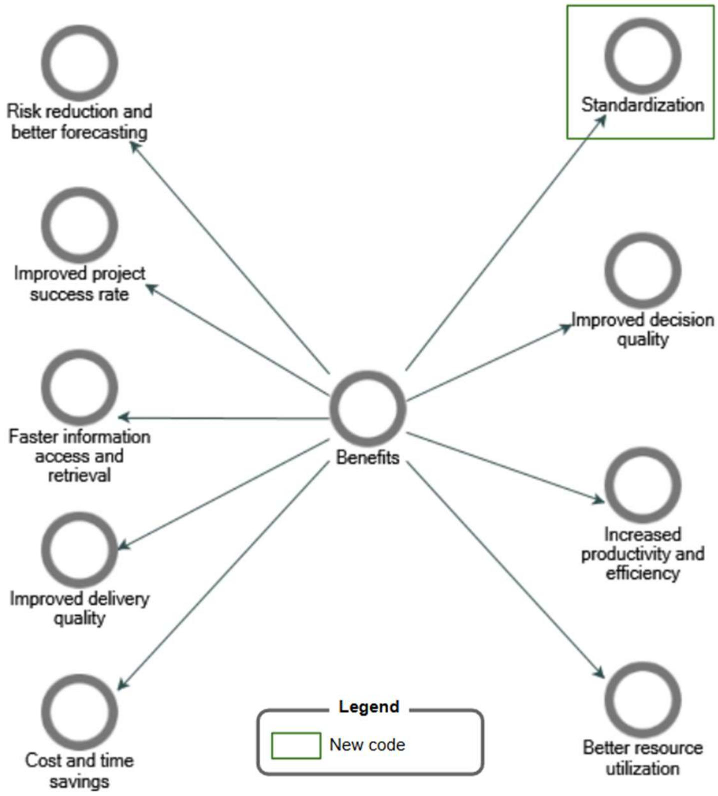
When comparing the frequency of mentions in Table 3, from the literature review, with Figure 8, from the empirical data, some similarities and discrepancies emerge. Applications such as Reporting and documentation and Communication and Collaboration appear prominently both in the interviews and in the literature. On the other hand, the literature highlights Scheduling, Decision-making and Risk Identification and Management as widely discussed applications (counts of 9). In contrast, these applications appear in fewer companies in the empirical dataset (2, 3 and 3, respectively). A significant discrepancy arises regarding Cost management and Resource allocation. In the literature summary, these two applications appear with relatively high frequencies (counts of 6 and 8, respectively), indicating their relevance as theorized applications of AI in project management. However, in the empirical data from this study, these applications were not mentioned by any company.

Overall, the treemap underscores that AI adoption across companies is concentrated in tasks that augment knowledge work and streamline workflows, while more technically demanding or analytically intensive applications remain less prevalent. This distribution reflects a gradual and incremental process of organizational learning, in which AI is first adopted for low-risk, high-utility tasks before expanding toward more complex project management functions.

4.4 AI Benefits

Figure 9 presents the coding structure for the category Benefits, synthesizing all interview segments referring to the perceived advantages of AI adoption across the five companies. The figure displays a set of nine benefit categories emerging from the data, each represented as a subnode linked to the parent node Benefits. The distribution of nodes illustrates the breadth of value attributed to AI in project environments.

Figure 9 - Benefits Coding



Source: Created by the author using NVivo.

Most benefits mentioned in the interviews correspond to expected outcomes frequently cited in the literature, such as risk reduction and better forecasting, improved delivery quality, cost and time savings, better resource utilization, improved decision quality, and increased productivity and efficiency. Their presence across multiple interviews indicates that AI is predominantly perceived as a tool that accelerates processes and strengthens decision-making capabilities, key levers of project performance.

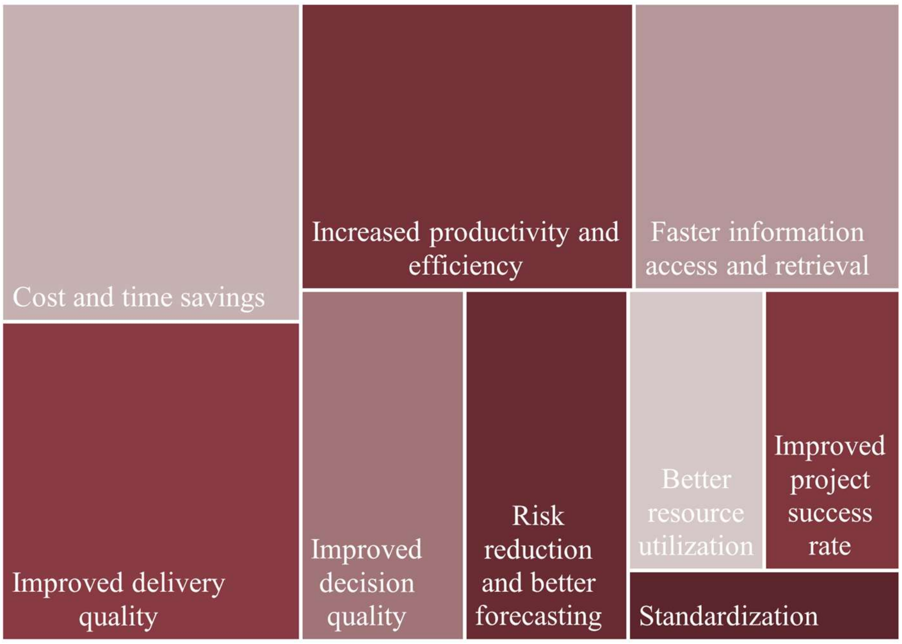
A new code emerged inductively during the analysis: standardization. Its appearance suggests that AI is seen not only as a means to optimize tasks, but also as an enabler of more uniform practices, harmonized outputs, and reduced variability across teams and project stages:

> There is a clear gain in standardization that is being noticed, for example when generating documentation that follows a specific format. (C02, author's translation)

The benefits identified reflect a multidimensional understanding of AI's contribution to project work, spanning operational efficiency, informational improvements, and enhanced strategic decision-making. The inclusion of an emergent code points to an evolving perception of AI as a mechanism for both productivity gains and organizational alignment.

Figure 10 illustrates how the perceived benefits of AI adoption are distributed across the five companies.

Figure 10 - Frequency-Based Visualization of Perceived AI Benefits



Source: Created by the author.

Three benefits, cost and time savings, improved delivery quality, and increased productivity and efficiency, stand out as the most frequently mentioned, each cited by five companies. The lexical patterns observed in the interviews further reinforce these findings: terms associated with the identified benefits dominate the discourse, with “time” appearing 39 times, “fast” 22 times, and “productivity” 22 times, each used with consistently positive connotations. Their prominence in the visualization underscores the central role of operational efficiency in motivating AI implementation.

One interviewee highlighted how AI has accelerated technical activities and iterative learning cycles within projects, noting:

> From a development standpoint, we shorten a lot of things. We shorten the search for references and, especially on the technical side, we shorten the whole process. I know this is not as common in management, but coding and testing things today is much faster. We can do in a single day what used to take us weeks, using the right tools. So this cycle of testing, validating, and then evaluating from a project perspective which approach is the most viable becomes much faster. (C03, author’s translation)

Another interviewee emphasized how generative AI has elevated collective performance by improving access to structured information, stating:

> I think it raises the bar for overall team performance. This happens because everyone now has access to a large amount of information, and it is structured. On Google the information was somewhat unstructured; you had to click through, read several websites and so on. Today, AI gives you a consolidated initial answer that strengthens your knowledge base. (C05, author’s translation)

These benefits reflect organizations' expectations that AI will streamline workflows, reduce execution time, improve output consistency, and support higher overall performance, aligning with findings reported in recent industry studies.

A second group of benefits, mentioned by three or four companies, includes faster information access and retrieval, improved decision quality, and risk reduction and better forecasting. These areas are represented by medium-sized rectangles in the treemap. Their frequency suggests that, beyond pure efficiency, companies also value AI's capacity to enhance informational processes and analytical precision. These benefits often depend on the maturity of internal data management practices and the integration of AI tools with existing information systems, which may explain their more uneven distribution across firms.

C04, which created a dedicated monitoring center focused on risk reduction, emphasizes the benefits already achieved with AI adoption:

> I truly see a reduction in accidents and greater agility in managing deviations […] You can see in our indicators a reduction of more than 50 percent in accidents. So I cannot say this remains only at the management level or anything like that. It has genuinely had an impact in the field, on the final outcome. (C04, author's translation)

Two benefits were mentioned by only two companies: better resource utilization and improved project success rate. Their smaller representation indicates that while these outcomes are theoretically associated with AI-driven project management, they may not yet be fully realized in practice or may require more advanced, data-intensive AI applications such as predictive analytics or resource optimization systems. These tasks generally involve higher implementation complexity, which could account for their limited presence among the companies studied.

Finally, standardization was mentioned by only one company, consistent with its status as an emergent code identified during qualitative coding. Although less prevalent, its presence suggests that AI may also serve as a mechanism for harmonizing processes and reducing variability in deliverables, a benefit that may become more pronounced as organizations advance in AI maturity.

Overall, the benefits identified reflect a balanced combination of efficiency gains, informational improvements, and enhanced analytical capabilities. The distribution patterns suggest that AI adoption in the studied companies is still largely concentrated on high-impact, low-barrier applications, while more complex or strategic benefits are emerging more gradually as organizations deepen their experience with AI tools.

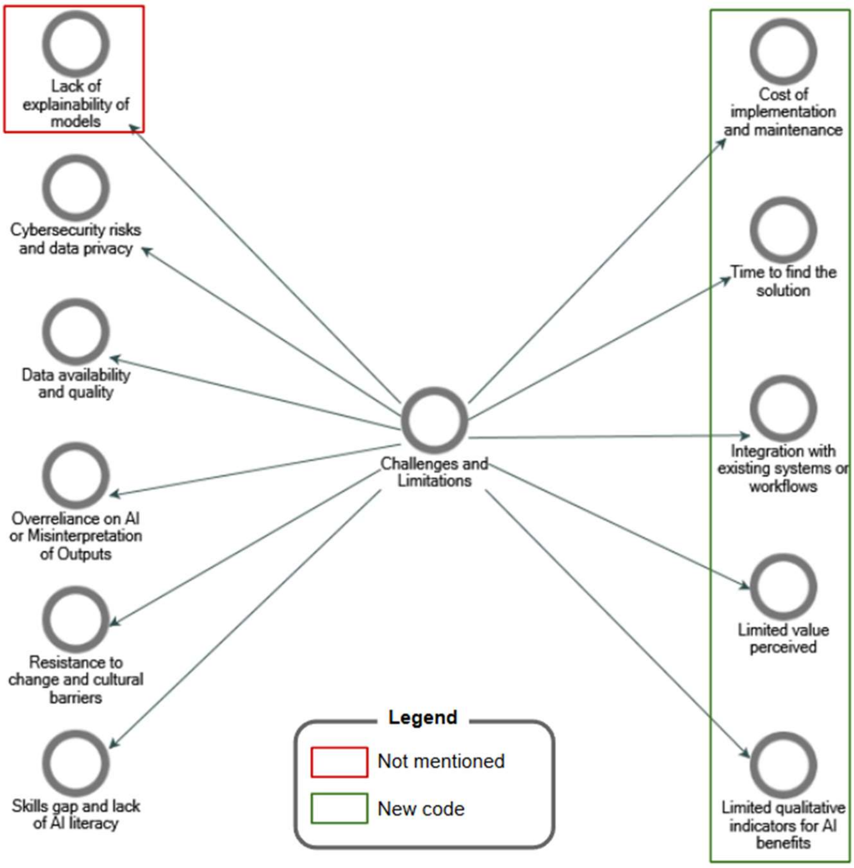
Across the five cases analyzed, interviewees consistently perceived AI as a source of competitive advantage, though the mechanisms through which this advantage materializes differ according to each company’s strategic posture, maturity, and operational context. In general, respondents associated competitiveness with AI’s ability to accelerate delivery, elevate analytical depth, and enable a more differentiated, higher-value service offering.

For some companies, the competitive edge emerges primarily from efficiency gains: by automating time-intensive tasks and improving the accuracy and consistency of deliverables, AI allows teams to reallocate effort toward activities that have direct strategic relevance, thereby increasing execution speed in bid preparation and project support. Others frame advantage more cautiously but still recognize that AI strengthens organizational performance when embedded in robust processes. Taken together, even with limited quantitative indicators for this advantage, the interviews reveal a shared belief that AI does not merely enhance internal productivity but increasingly shapes market positioning, differentiating firms that learn to integrate it effectively from those that lag behind in adoption.

4.5 AI Challenges and Limitations

Figure 11 displays the coding structure for Challenges and Limitations, capturing the main obstacles perceived by the companies in adopting and integrating AI into project work. Most challenges reflect well-documented concerns in the AI literature, such as cybersecurity risks and data privacy, data availability and quality, overreliance or misinterpretation of outputs, resistance to change, and skills gaps, indicating that organizations face a combination of technical, cultural, and capability-related barriers.

Figure 11 - Challenges and Limitations Coding



Source: Created by the author using NVivo.

The figure includes a set of new codes, shown in green, which emerged inductively from the interviews: limited qualitative indicators for AI benefits, limited value perceived, integration with existing systems or workflows, time to find the solution, and cost of implementation and maintenance. These highlight practical and operational challenges that are shaped by each company's current level of digital maturity and resource constraints.

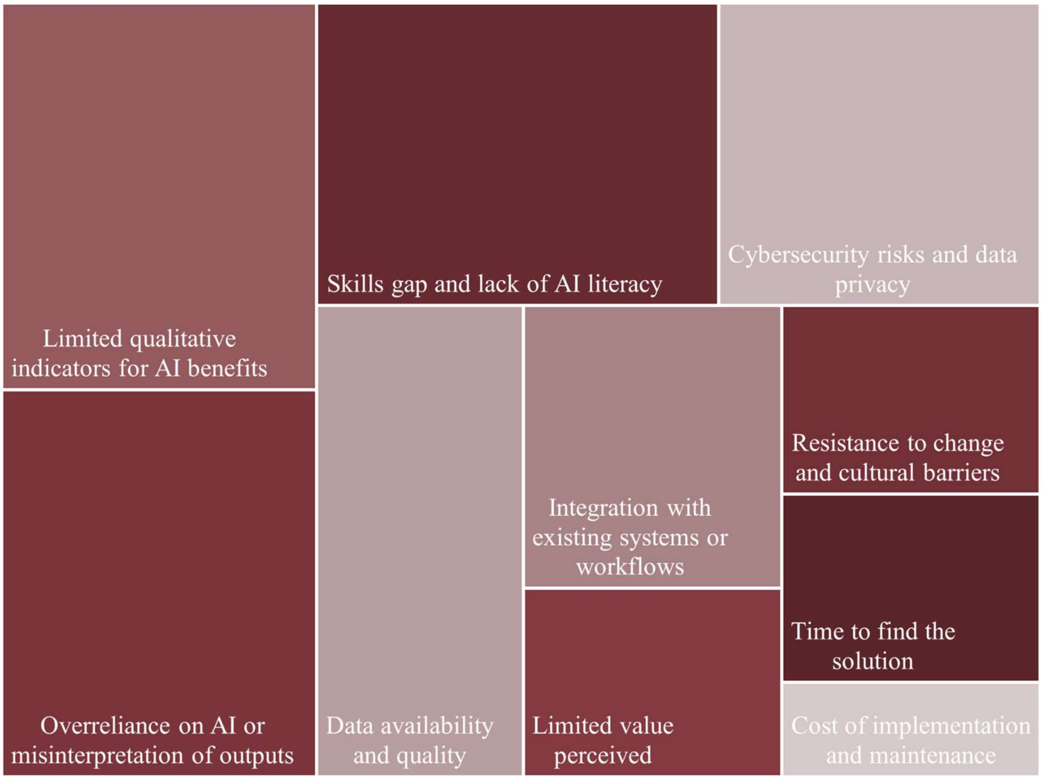
The limited value perceived is related to time to find the solution and is explained by this interviewee:

> In my view, what makes me use it less is when I am about to do something that would take me five minutes on my own, but I would spend five minutes writing a prompt for the AI and another five minutes reading the answer. For me, it is not worth it because I end up losing time. So when I do not have a clear, objective value in the task, when I am not confident that the AI will give me a better or faster result that will actually be useful, I simply do not use it. In terms of innovation, I might be able, by spending time on it and trying several approaches, to reach a very good outcome that could automate a future process, but I honestly do not prioritize that today. I think it has more to do with not seeing clear, objective value. I do not usually use it just for the sake of using it to see if the result turns out interesting. (C02, author's translation)

In contrast, the only challenge not mentioned by any interviewee, lack of explainability of models, is outlined in red. Its absence is notable given its prominence in academic debates, suggesting that, in these companies, concerns about transparency are less salient than issues related to usability, integration, and day-to-day operational demands, mainly because it is a more technical issue than a practical one.

The treemap in Figure 12 provides a clear overview of the main challenges and limitations perceived by the companies in adopting and integrating AI into their project workflows. Three challenges stand out as the most frequently mentioned: limited qualitative indicators for AI benefits, overreliance on AI or misinterpretation of outputs, and skills gap and lack of AI literacy, each cited by five companies.

Figure 12 - Frequency-Based Visualization of AI Challenges and Limitations



Source: Created by the author.

One interviewee underscored that the primary constraints to effective AI adoption stem not from the technology itself but from human capability and literacy, explaining:

> I think the biggest limitation of artificial intelligence today is our own intelligence. We do not yet know how to use the available tools in the best way, and we are still learning. I believe the technology is evolving faster than we can keep up with. [...] There is also a literacy component. If I give a poor prompt, the answer will be poor. So I need to know how to teach people to use it in the best possible way. (C03, author's translation)

They also emphasized the difficulty when measuring the benefits, even in big tech companies such as Google:

> I think the benefit is much greater than what we can currently quantify [...] It is a very difficult number to obtain. I really want us to get there someday. I am talking with the

> team about structuring this study so that we can make it concrete and say something like ‘AI makes the company 10 percent more productive, 20 percent more productive.’ I know it increases productivity, but I do not know by how much. [...] There is a major challenge in measuring this. At Google, they have a dedicated unit for this purpose, and they review the numbers regularly. In the beginning the numbers were much more extreme, like 200 percent productivity gains. Now there are other studies saying: ‘If you apply it well, it is 25 percent.’ So the ranges vary a lot, and it is very hard to measure because no one wants to be a control group, no one wants to do a project twice, one without AI and the other with AI, just to compare. (C03, author’s translation)

Their prominence suggests that organizations are struggling simultaneously with measurement difficulties, risks related to improper use, and capability deficits. Together, these issues reflect the tension between rapid adoption and the slower pace of organizational learning and governance development.

A second group of challenges, cybersecurity risks and data privacy and data availability and quality, was mentioned by four companies. These concerns indicate that, beyond skills and usage patterns, technical and infrastructural constraints remain significant barriers. As AI tools increasingly interact with sensitive data and internal systems, organizations appear to be aware of the need for stronger data governance and information security practices.

Other challenges appear with a more selective distribution. Integration with existing systems or workflows was mentioned by three companies, highlighting that technical alignment and interoperability pose difficulties for organizations with heterogeneous digital environments. Meanwhile, limited value perceived, resistance to change and cultural barriers, and time to find the solution were noted by two companies each, pointing to organizational and behavioral factors that affect adoption beyond purely technical constraints.

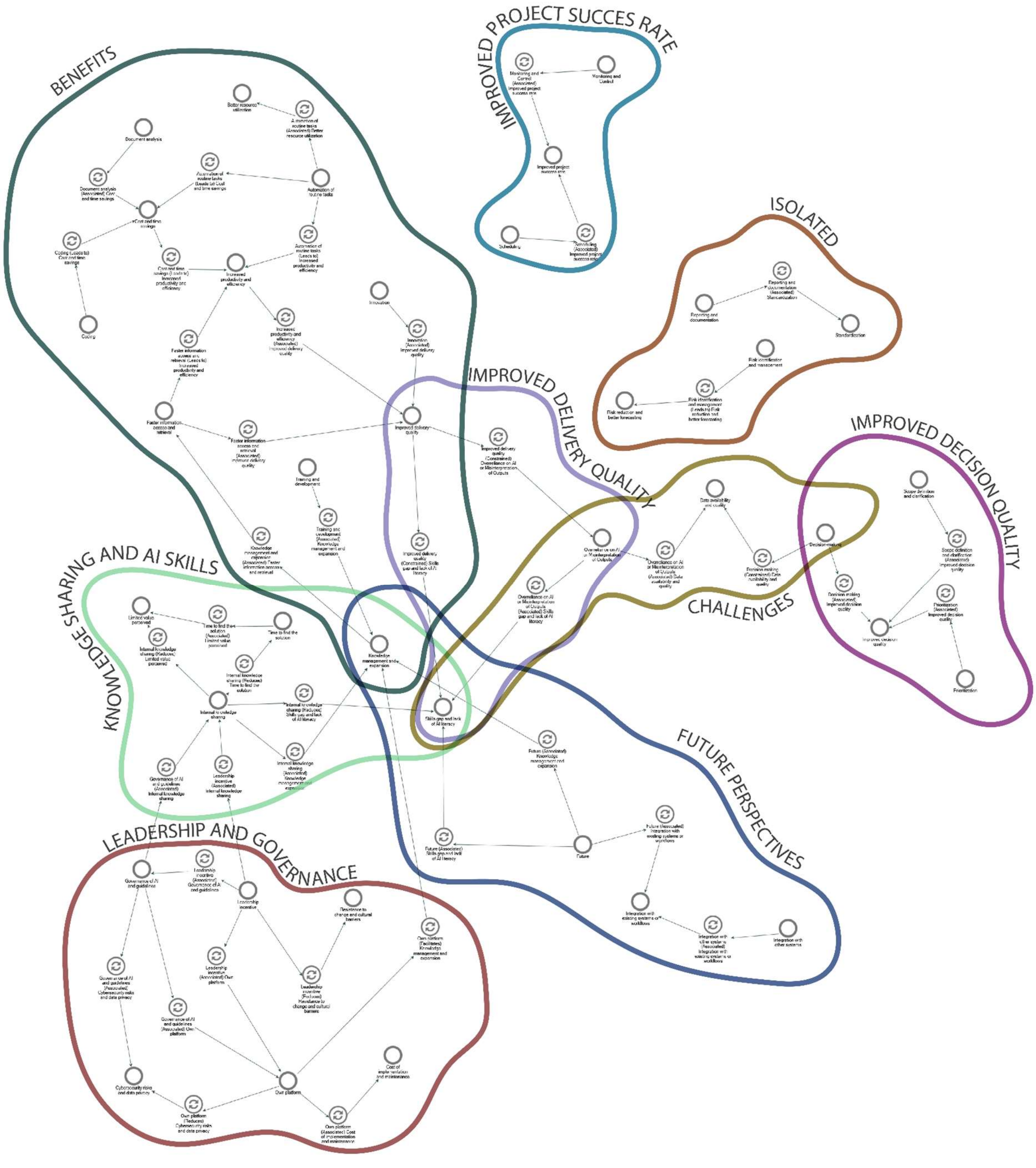
Lastly, cost of implementation and maintenance was mentioned by only one company, C05, the smallest one, which suggests that, in this sample, financial considerations are less prominent than operational or human-related challenges. This may be because companies already perceive substantial value in AI’s contribution to daily work routines, leading them to view the associated costs as justified or offset by the benefits.

Overall, the distribution of challenges reveals that the most pressing barriers for the companies lie in building internal competencies, ensuring appropriate use, and developing mechanisms to evaluate AI’s value, rather than in abstract model limitations or financial constraints. The pattern suggests that organizational readiness and capability development remain the key determinants for effective and sustainable AI adoption.

4.6 Relationships across applications, benefits and challenges

All relationships identified during the coding process can be seen in Figure 13 below. A table summarizing them is also presented in Appendix C. To improve visualization, smaller maps were created by zooming into each area (shown in different colors below), according to themes, and they are presented and explained throughout the subsequent sections.

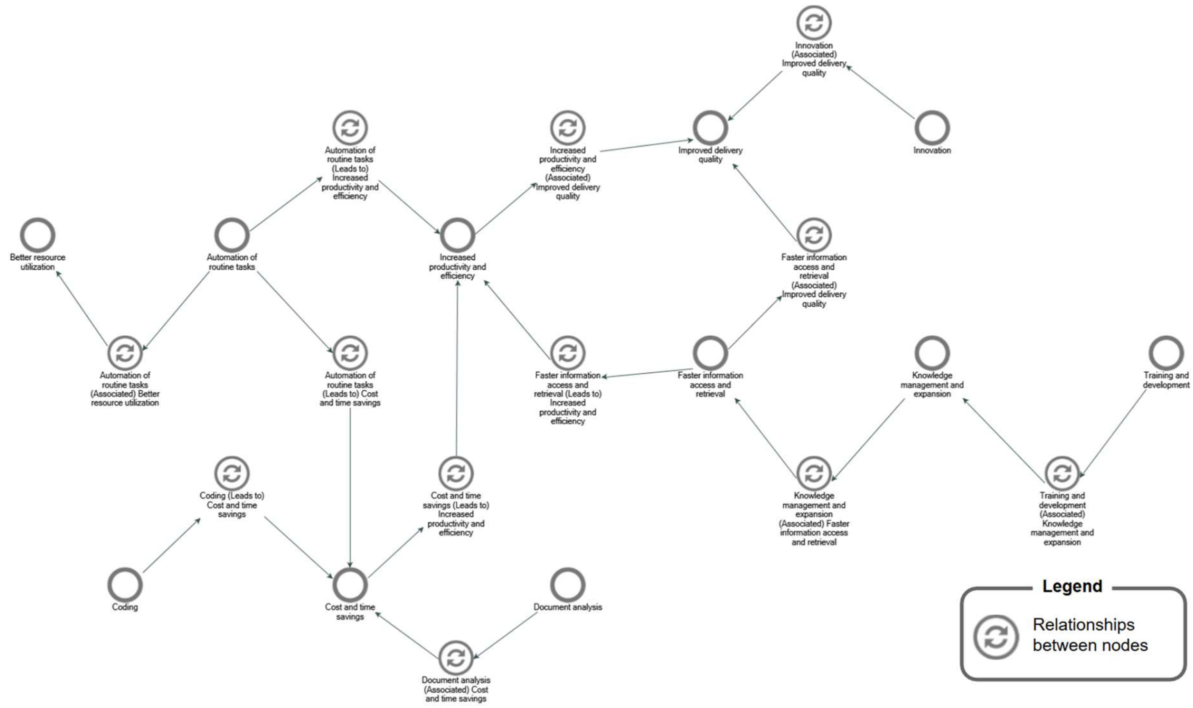
Figure 13 - All relationships identified



Source: Created by the author using NVivo.

Figure 14 presents an interconnected network of relationships that explains how different applications of AI translate into concrete organizational benefits. At its core, the model demonstrates that the benefits of AI do not emerge from isolated use cases; instead, they result from the cumulative and reinforcing interactions among automation, information processing, and knowledge management capabilities. The logic behind these relationships reveals a coherent chain of value creation in which AI progressively reduces manual effort, accelerates information flows, and enhances the quality and efficiency of project work.

Figure 14 - Benefits relationships



Source: Created by the author using NVivo.

The first and most central pathway originates from automation of routine tasks, which appears as a fundamental mechanism across all companies. Automating repetitive, low-value activities leads directly to cost and time savings, as employees spend less time on manual preparation, formatting, or operational steps. These savings then cascade into increased productivity and efficiency, because teams can reallocate time to higher-impact analytical or strategic work. Automation also supports better resource utilization, since workforce capacity is optimized and fewer hours are consumed by administrative tasks.

In essence, automation acts as the engine that unlocks the initial productivity gains associated with AI adoption. This relation can be seen in this citation:

> At the end of the day, productivity comes from a balance between quality, which I believe people are now able to deliver at a higher level, with fewer mistakes and more revision. So the top part of the equation, quality, naturally increases. And on the bottom, people save resources, time, their own working hours. In practice, it results in a productivity boost [...] productivity, quality, and time. (C03, author's translation)

Complementing automation, applications such as coding assistance and document analysis similarly contribute to this efficiency pathway. Coding tools reduce the cognitive and temporal burden of developing scripts, prototypes, or automations, thereby reinforcing the flow toward cost and time reductions. Document analysis, automated extraction, summarization, or pattern recognition, reduces the need for manual reading and interpretation. These applications also strengthen the central productivity loop by improving the speed and accuracy of information processing, which further amplifies operational efficiency.

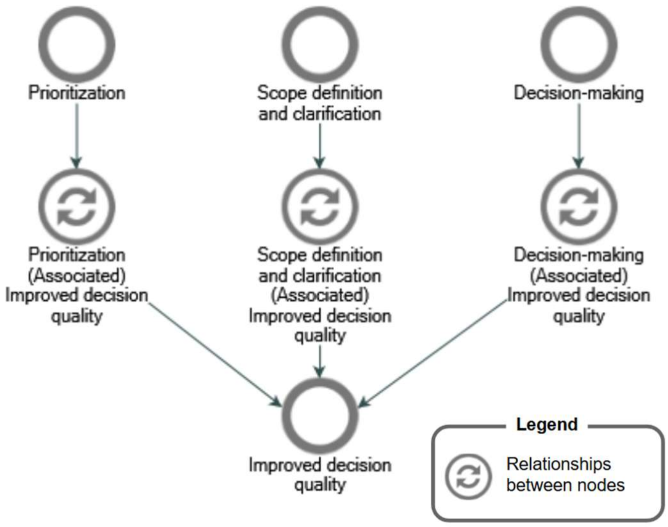
A second major pathway emerges from faster information access and retrieval, which is both a result of and a contributor to improved knowledge processes. AI tools enable quick retrieval of historical cases, project materials, or contextual information that would otherwise require considerable manual search time. As this information becomes more accessible, teams experience a measurable increase in productivity: decisions are made more quickly, planning becomes more informed, and bottlenecks caused by slow information flows are reduced. Faster access is also associated with improved delivery quality, as better and timelier information reduces errors, supports more aligned deliverables and enhances the possibilities of innovation, with broader references.

Underlying and reinforcing this acceleration is knowledge management and expansion, which represents a more strategic layer of AI application. When AI systems help organize, systematize, and expand the organizational knowledge base, they provide the informational foundation required for faster retrieval and more consistent decision-making. This creates a self-reinforcing loop: enhanced knowledge management leads to more reliable and accessible information, which in turn improves productivity and quality; the improved outputs then feed additional data and insights back into the knowledge base, strengthening it over time. Moreover, AI is also leveraged for training and development purposes, as employees use these tools to draft personal development plans and to strengthen specific competencies, thereby supporting internal knowledge management and professional growth.

Together, these interconnected pathways illustrate a coherent value logic: AI applications that automate and structure work processes reduce operational effort, which increases productivity; AI applications that enhance information flows improve decision accuracy and delivery quality; and AI applications that expand organizational knowledge strengthen long-term capacity and consistency. The combined effect is a multi-layered system in which efficiency, quality, and resource utilization are continuously improved through mutually reinforcing mechanisms enabled by AI.

Figure 15 highlights an additional set of relationships demonstrating how AI contributes specifically to improved decision quality by enhancing core project management activities. Three applications, prioritization, scope definition and clarification, and decision-making support, each play a distinct yet complementary role in strengthening the accuracy, consistency, and reliability of project-related decisions.

Figure 15 - Improved decision quality relationships



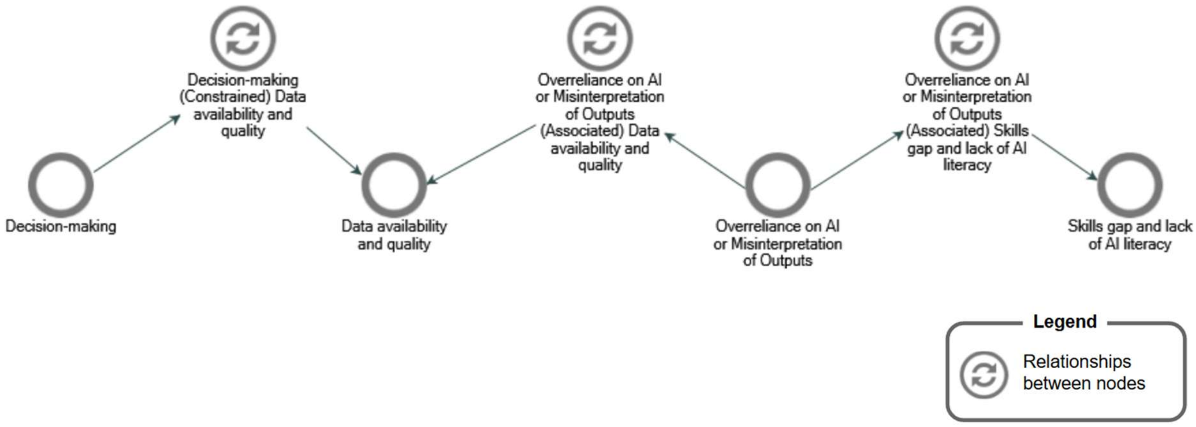
Source: Created by the author using NVivo.

AI-assisted prioritization helps teams identify what matters most by quickly analyzing alternatives, synthesizing criteria, and highlighting the relative importance of tasks or issues. This reduces ambiguity and supports more rational, evidence-based choices, which directly contributes to higher-quality decisions. Similarly, AI tools that assist in scope definition and clarification help identify gaps, inconsistencies, or unclear requirements early in the process. By refining the scope with greater precision, teams avoid downstream misunderstandings and ensure that decisions are grounded in a more accurate understanding of project needs and constraints.

Finally, AI-enabled decision-making support empowers teams by offering scenario analysis, data-driven insights, and rapid synthesis of complex information. This capability does not replace human judgment but strengthens it, ensuring that decisions are made with broader visibility and better contextual understanding. Together, these three applications feed into a central outcome: improved decision quality, achieved through clearer priorities, more precise scoping, and more informed evaluations. This set of relationships illustrates how AI enhances the cognitive and analytical foundations of project work, ultimately leading to more robust and defensible decisions.

Additionally, Figure 16 consolidates the main relationships identified between the challenges and applications reported by the interviewees, revealing a network of mutually reinforcing constraints that shape the effectiveness of AI adoption in project environments. A central theme emerging from these links is that several challenges act cumulatively, amplifying the overall difficulty of embedding AI into daily workflows.

Figure 16 - Challenges and limitations relationships



Source: Created by the author using NVivo.

One of the first relationships illustrated concerns the dependency between decision-making and data availability and quality. Interviewees highlighted that AI-assisted decision-making is constrained when organizations lack structured, reliable, or sufficiently comprehensive data, since AI outputs become less trustworthy and require greater human effort for validation. This challenge is further connected to the issue of overreliance on AI or misinterpretation of outputs, which is associated with data quality concerns: when datasets are incomplete or inconsistent, the risk of misinterpreting AI results increases, especially if users assume that the system will "fill in the gaps."

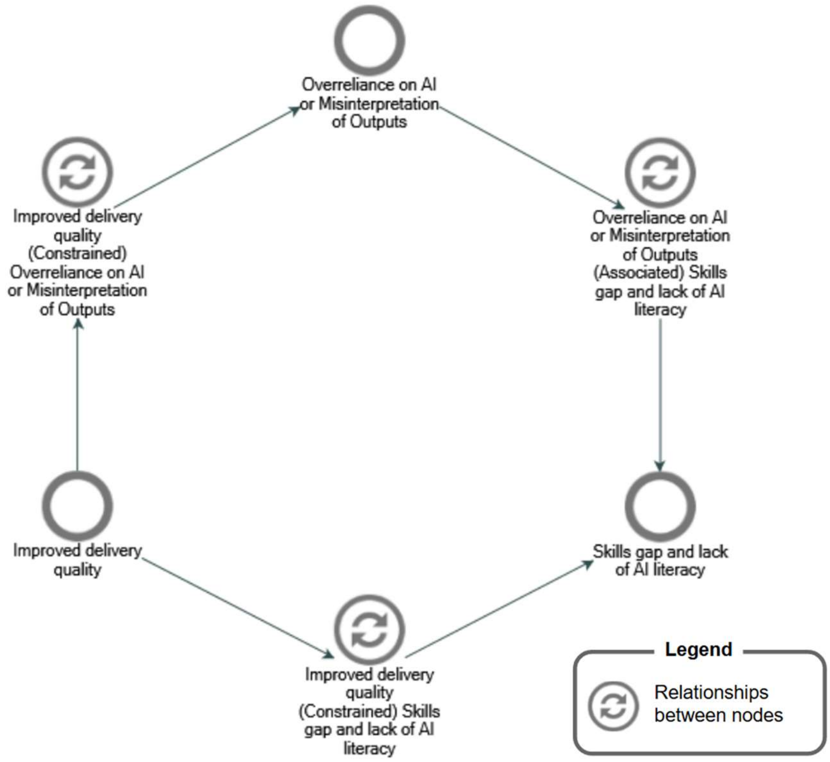
Another set of relationships highlights the interplay between skills gaps, lack of AI literacy, and overreliance on AI. Overreliance is associated with limited technical understanding, illustrating a reciprocal dynamic in which insufficient literacy not only elevates the risk of misinterpretation but also encourages users to depend excessively on AI systems without applying critical judgment.

Collectively, the relationships depicted in the figure show that challenges related to AI adoption do not operate in isolation but instead form a system of interconnected constraints.

Skills deficits increase the risk of overreliance; poor data quality amplifies misinterpretation; and decision-making is constrained by low data availability and quality.

An additional relationship is depicted in Figure 17, pertaining to the benefit of improved delivery quality. The figure shows that improved delivery quality is dependent on two conditions: avoiding overreliance on AI or misinterpretation of its outputs, and reducing the skills gap and lack of AI literacy. These challenges act as constraints, meaning that delivery quality can only be achieved when users critically review AI outputs and possess adequate technical competence. The relationships also reinforce one another: limited skills increase the risk of misinterpretation, while excessive dependence on AI further weakens users' skills. Overall, the diagram emphasizes that human capabilities remain essential for realizing the benefit of improved delivery quality.

Figure 17 - Improved delivery quality constraints

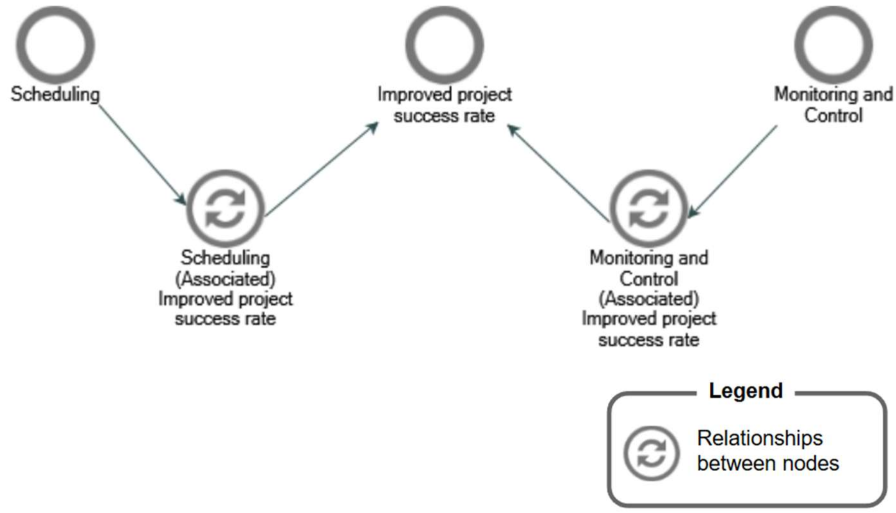


Source: Created by the author using NVivo.

Moreover, Figure 18 illustrates that improved project success rate is closely associated with two key applications of AI: monitoring and control, and scheduling. Both relationships are associative, indicating that these practices contribute to enhanced outcomes but do not independently guarantee them. AI-supported monitoring and control strengthens project oversight, while AI-enabled scheduling improves planning accuracy and smarter changes.

Together, these capabilities reinforce one another by increasing project visibility and reducing uncertainty, ultimately supporting higher success rates.

Figure 18 - Improved project success rate relationships



Source: Created by the author using NVivo.

4.7 Leadership and Governance

Across the organizations analyzed, the adoption and diffusion of AI tools are strongly shaped by leadership incentives, the presence (or absence) of formal governance structures, and the mechanisms established to disseminate AI-related knowledge internally. The interviews reveal heterogeneous levels of maturity across companies but also clear patterns regarding how leadership engagement and governance models condition the organizational trajectory of AI adoption.

Leadership endorsement emerges as a primary driver of adoption, especially in contexts where bottom-up experimentation was initially prevalent. In C01, senior directors were highly engaged in the use of AI and indirectly incentivized the interviewee to begin exploring the technology. Leadership also initiates training activities, including internal workshops requested by the director to encourage best-practice sharing among technical and managerial staff.

> Indirectly, it happened through encouragement. In fact, both of our directors became very engaged with AI as soon as all of this started. Then I began looking into it as well, around two years ago. (C01, author’s translation)

Similarly, C02 signals strong top-down encouragement. Although not mandatory, leadership frames AI use as an expected and increasingly standard capability, particularly in proposals and analytical projects, promoting an open environment in which everyone can use it rather than restricting access. In C04, leadership incentive comes in an explicitly hierarchical form, with directives establishing clear expectations for tool usage and centralizing decisions on which AI models may be used.

C03's leadership has shown strong encouragement for the use of AI, beginning in 2021 when the company created a new division dedicated to projects in this domain. The organization developed its internal AI platform as a result of leadership initiative and maintains multiple training programs to ensure that knowledge is broadly disseminated.

Conversely, C05 adopts a more experimental, founder-led logic where fast, low-cost testing replaces formal leadership programs. Decisions on AI tools are fast and experimentation is encouraged with minimal discussion, reflecting a startup environment where leadership fosters agility rather than formal guidance.

> Decisions about using AI are made very quickly. We usually spend very little time discussing them, as long as they're inexpensive, we test a lot. There are no restrictions on which tools to use or when to use them, what matters is making your daily work easier without compromising delivery quality. (C05, author's translation)

The presence and rigor of governance structures vary substantially. C02 demonstrates the most robust governance mechanisms, including explicit restrictions on tool choice, monitoring of unauthorized tools to prevent data leakage, and the existence of multiple governance bodies: an AI committee, a governance team, and an enabling team responsible for corporate AI tools. This model illustrates a mature governance architecture balancing autonomy with compliance controls.

> It's a company guideline, we're only allowed to use Gemini. […] as long as we stay within the approved tools, each area has its own autonomy. […] but there is a team that oversees the policy, sets restrictions, and monitors everything. So, for example, if I log into my computer and open ChatGPT, the group sees that, you're being remotely monitored and so on, to avoid exposing sensitive data. Within the approved tools, you can use them however you want. On the other hand, you must follow the defined policies. There is an AI committee, an AI governance team, and an enablement team that manages the corporate Gemini environment and our other AI tools as well. (C02, author's translation)

C01 also displays governance awareness, particularly concerning client-side policies. Teams refrain from using AI tools when client restrictions apply, especially for confidential documents, reflecting a decentralized but risk-sensitive governance culture.

C03 indicates that the company does not operate under an explicit guideline defining when AI should be formally incorporated into a project. Instead, it embraces a broad, opportunity-oriented view in which AI can be applied virtually anywhere, provided that data privacy and leakage risks are carefully managed. The availability of the internal AI platform and the provision of a premium corporate license function simultaneously as incentives for adoption and as governance mechanisms, enabling widespread experimentation while maintaining controlled and secure use.

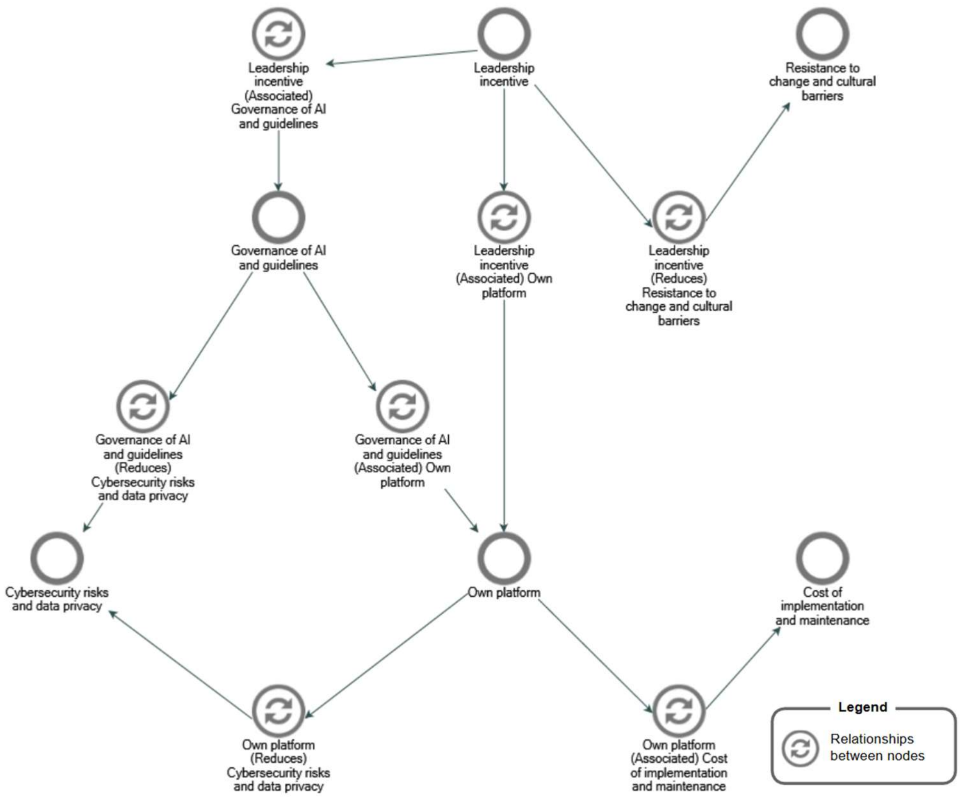
> We don't have a guideline that says, 'You must use AI,' or that every proposal has to include it. We don't. But we've been seeing a push for that to happen already in the proposal stage. Today it's very hard to imagine any process-mapping or data-analysis project that doesn't require people who understand AI, analytics, and so on. So I don't think it ever came as a mandate; it just naturally evolved that way. […] to make it concrete: in the proposal or pre-proposal phase, if it makes sense, it will be included, and we almost always include it because it's hard to think of a case where it wouldn't make sense. And once you're in a project, no one is going to be prevented from using AI. (C03, author's translation)

C04 follows a centralized, corporate governance structure originating from headquarters, ensuring alignment with global standards but offering local teams significant autonomy for everyday uses such as summarizing meetings or drafting documentation.

In contrast, C05 presents a near absence of governance mechanisms: there are no data-protection protocols and no limitations on model learning, reflecting an early-stage governance maturity where speed and experimentation override formalized safeguards.

Figure 19 illustrates a set of interconnected causal relationships in which leadership and governance occupy a central and mutually influential position.

Figure 19 – Leadership and Governance relationships



Source: Created by the author using NVivo.

Governance of AI and guidelines is closely associated with leadership incentive, suggesting that clear, structured, and well-defined governance frameworks tend to stimulate leadership engagement. When leaders operate within a coherent governance environment, they are more likely to promote alignment, encourage compliance, and foster organizational coherence. In turn, leadership incentive plays an important role in reducing resistance to change and cultural barriers. As leadership becomes more active and motivated, employees tend to feel more supported and guided, which decreases hesitation toward new technologies or processes. The relationship, however, also works in reverse, resistance to change can weaken leadership incentive, indicating a reinforcing loop in which cultural stagnation undermines leadership efforts, which then fails to further reduce resistance, perpetuating an organizational impasse. Within this set of relations, governance also reduces cybersecurity risks and data privacy concerns, demonstrating that robust rules and guidelines help create a more secure digital environment that strengthens leadership's credibility and capacity to promote technological adoption:

> The concern with confidentiality is quite significant. The group's data ecosystem is very complex, and we end up handling a lot of information, including personal and sensitive data, so we enforce this restriction. Company data does not go outside, it does not feed into Google's training, precisely to avoid inadvertently sharing consumer data, for example. That would be unacceptable, so the rules are very strict in that regard. (C02, author's translation)

Once these leadership and governance dynamics are established, the diagram shifts focus toward the organizational platform and its associated elements. Governance of AI and guidelines, now functioning as a stabilizing force, is associated with the development or reinforcement of the organization's own platform. Better governance provides direction, standardization, and clarity for platform design and use. Leadership incentive emerges as a central catalyst: it reduces cultural resistance, motivates experimentation, and stimulates the development of an internal AI platform, which in turn further strengthens leadership engagement. This platform also supports the establishment of governance structures, both by enabling secure environments that mitigate cybersecurity and data-privacy risks and by formalizing rules on tool usage. Strong governance and guidelines then reinforce organizational confidence in AI, contributing to safer experimentation and more consistent practices.

4.8 Internal Knowledge Sharing and Capability Development

Internal knowledge sharing appears as a widespread organizational strategy, though with different levels of formality. C01 invests in peer-driven learning, where employees who gained proficiency in AI deliver training and share use cases, encouraging collaborative idea exchange during workshops.

> Last year, I gave a training session on everyday AI use, and some people here still tell me, ‘I started using ChatGPT because of you.’ […] recently our director asked us to run a workshop with both technical staff and managers to share information. Because even in that training, I usually say, ‘I’m going to give you examples of use cases so it’s easier to visualize them in your own context,’ but sometimes I show something, a use case of mine, that people hadn’t considered yet. And in these small-group discussions, at some point during the training, either midway or at the end, if someone has an interesting use case or something that worked well, they share it. (C01, author’s translation)

C02 demonstrates a multi-layered knowledge-sharing ecosystem, combining large-scale initiatives such as “AI week” (a week-long company-wide training), formal corporate education platforms, external learning tools (Google, Udemy), and community-oriented structures such as product chapters and tech talks where employees frequently present AI-related cases.

C03 faces challenges in institutional knowledge retention. Although there is a formal figure named Learning Organization that centralizes best practices, the company admits it often prioritizes delivery over documentation, which constrains systematic knowledge sharing. Knowledge is therefore partially embodied in senior partners who act as carriers of contextual expertise across projects. While effective, this limits scalability and raises concerns about organizational dependency on individuals.

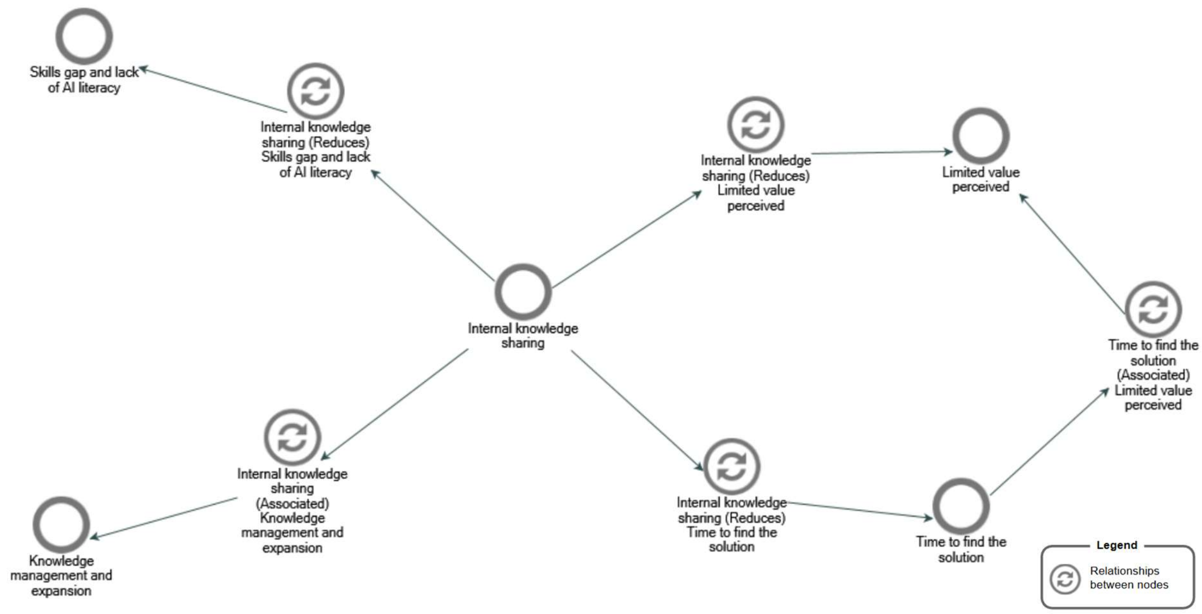
C04 adopts an outward-facing approach to knowledge dissemination: the control center hosts external visits, emphasizing societal and safety-driven sharing beyond organizational boundaries.

> After we inaugurated our monitoring center, we started receiving frequent visits from people interested in learning about it. […] it’s open exactly so we can share knowledge with other people and other companies. Because, in the end, our real goal is to prevent accidents. (C04, author’s translation)

Finally, C05 again stands out for its absence of structured knowledge-sharing mechanisms, reflecting a startup environment that values speed over process formalization.

Figure 20 illustrates a network of mutually reinforcing relationships. Knowledge sharing simultaneously reduces the skills gap, enhances perceptions of value, and shortens the time required to find solutions. In contrast, limited value perceived and long search times tend to inhibit knowledge sharing and weaken its benefits. Together, these elements form a dynamic structure in which improving internal knowledge sharing can break negative cycles and generate positive momentum for organizational learning, efficiency, and the adoption of AI-related practices.

Figure 20 – Knowledge sharing and AI Skills



Source: Created by the author using NVivo.

At one end of Figure 20, the skills gap and the lack of AI literacy appear as initial challenges. These challenges are mitigated when internal knowledge sharing increases, since sharing experiences, practices, and insights helps reduce the existing deficiencies in AI understanding. As employees exchange knowledge, the organization progressively closes the skills gap and strengthens its overall competence.

Figure 20 also shows that internal knowledge sharing also affects how individuals perceive the value of available tools, processes, or knowledge systems. When knowledge is shared more effectively, it reduces the perception of limited value, because people can better understand how resources help them in practice. However, the relationship is not unidirectional. Limited value perceived also influences internal knowledge sharing, creating a feedback loop. When employees believe the value of a system or knowledge base is low, they become less inclined to participate, share, or contribute. This, in turn, reinforces the initial perception and can weaken knowledge flows within the organization. Figure 20 also incorporates the role of the time required to find a solution. A longer search time tends to be associated with a stronger perception of limited value. If users struggle to locate solutions or need excessive time to obtain answers, their judgement of the system's usefulness diminishes. Conversely, internal knowledge sharing plays a crucial role in reducing the time to find solutions. When knowledge circulates more freely, employees spend less time searching because relevant information becomes easier to access. This reduction in search time also feeds back into the system: as it becomes quicker to find what one needs, individuals may become more motivated to engage in knowledge sharing, recognizing its practical benefits.

4.9 Future perspectives

The interviews reveal a shared understanding that AI will become increasingly embedded in organizational routines, ultimately shifting from a novel technology to an invisible infrastructure underpinning day-to-day work. Across companies, respondents anticipate a future characterized by deeper automation, expanded integration across tools, and a progressive reconfiguration of project management roles and capabilities.

As mentioned before, one perspective is that AI will evolve from being a specialized instrument into a pervasive, background technology, much like the internet or the smartphone today. The interviewee adds that the main limitation is not technological but human: people still do not know how to use existing tools to their fullest, and the pace of technological evolution exceeds the speed at which users can adapt.

Participants also foresee significant advances in automation. Some anticipate transformations substantial enough to alter operational structures, especially in technical environments. One respondent explains that, in the future, entire factories could operate autonomously, with human workers performing only supervisory tasks to ensure nothing malfunctions. This vision reinforces concerns that automation could displace workers in a nonlinear way.

> Because we work heavily with automation and technology, we already see the potential for fully automating a plant, reaching a point where it becomes autonomous and operations are reduced to monitoring, just to ensure nothing has stopped. That's when concerns about future job replacement begin to emerge. (C01, author's translation)

Beyond industrial automation, interviewees highlight the rise of autonomous AI agents capable of performing tasks directly on users' computers, such as selecting files, organizing folders, or executing workflows, suggesting that locally integrated agents will soon become an important capability.

> One of the things is the use of agents. You could ask ChatGPT to select a file from a folder and send it to destination X or Y depending on what it finds inside, things like that. Once I'm able to use that, it's going to be interesting. But ultimately, it's about using agents and enabling better integration between ChatGPT and your own computer. I think that part will be very interesting once it becomes available. (C01, author's translation)

In three of the interviews, a strong aspiration concerned native integration. Respondents emphasize the limitations of current tools, which often require navigating separate platforms, manually exporting outputs, or assembling workflows that AI cannot yet execute end-to-end.

For example, while generative models can outline a slide deck, they still cannot generate complete presentation files; while they can produce code prototypes, they often cannot export them seamlessly. Interviewees expect this to change soon, envisioning a future in which AI is fully embedded in productivity software, allowing direct slide creation, prototype exportation, or native functionality inside email, browsers, and enterprise systems.

> In my view, the future is about integration. It's about no longer treating AI as an isolated tool that you have to access through a separate URL or website, and instead having it natively embedded into things. For me, that's the key point. (C03, author's translation)

Another prominent theme relates to how project teams will be structured. Assuming technology remains at its current level for some time, respondents argue that every project should have at least one person able to rapidly build AI solutions, turning manual processes, such as meeting note documentation, into automated systems. In parallel, all professionals should develop the ability to discuss business implications of AI, not only its technical aspects. The future project environment therefore demands hybrid capabilities: technical fluency combined with business comprehension and critical reasoning.

> In my opinion, every project should have at least one person who can discuss AI effectively and implement something quickly, because we know the application is extremely broad and generalizable. I see many projects that would benefit greatly from having someone who can quickly put together a solution and turn something that used to be manual, like meeting notes or similar tasks, into an automated process. Large projects, I think, are already closer to that reality. […] beyond having someone who can develop or at least understands the basics, I also see another need: everyone should know how to discuss business with AI. Technical people should be able to talk about business impact and how things connect, and the reverse is also true. (C03, author's translation)

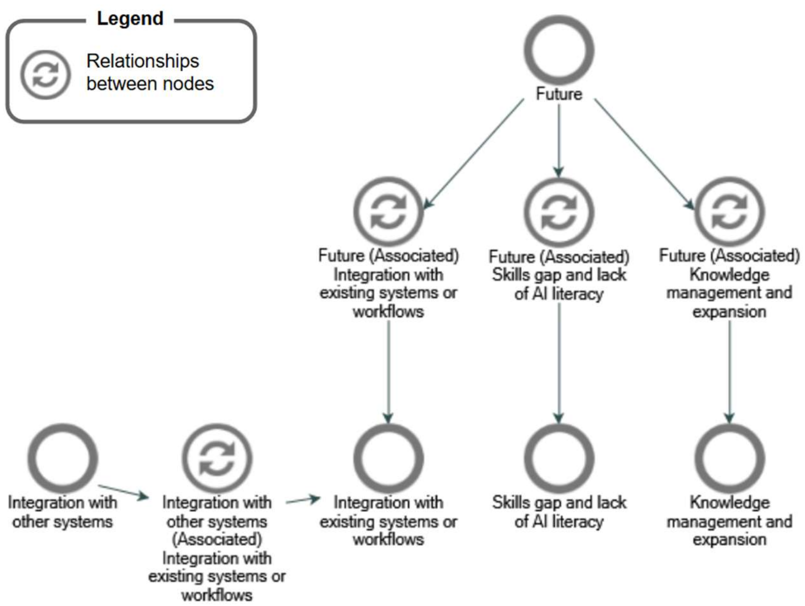
Some organizations also envision powerful domain-specific applications. In safety-critical contexts, for instance, respondents describe how years of incident reports, procedures, and safety logs could be aggregated into a closed AI system capable of immediately contextualizing new observations. When a worker reports a hazardous condition, such a system could automatically identify similar past occurrences, quantify their historical frequency and severity, and propose suitable corrective actions. This illustrates a future in which AI not only automates work but directly supports decision-making through organizational memory.

> We've carried out many procedures over these four years. […] If we took all this material and fed it into an AI model, turning it into a closed system, it could help us in situations like this: an employee reports seeing someone climbing a ladder with a missing step. Based on all the information we've gathered over four years, the AI could tell you something like: 'Given the information you just entered and comparing it to all existing records, you've already had X deviations related to this issue, or X accidents with severity levels X, Y, and Z on this same topic, and we recommend that you take the following actions. (C04, author's translation)

Finally, employees recognize that the rapid pace of innovation will require continuous learning. Tools are becoming obsolete quickly, and respondents caution against investing in expertise on a single tool. Instead, they emphasize the importance of learning how to learn, adapting to new models, keeping up with new features, and developing durable AI literacy. The future is seen as dynamic: technologies evolve rapidly, capabilities emerge continuously, and the skills required today will likely differ from those required in the near future.

Summarizing the future perspectives shared by the interviewees, there is an expectation that AI will become seamlessly embedded into project environments, yet this trajectory is tightly connected to three core nodes that shape how such a future can materialize, as shown in Figure 21.

Figure 21 - Future perspectives relationships



Source: Created by the author using NVivo.

First, the aspiration for natively integrated, end-to-end AI solutions directly relates to the current difficulty of integrating AI with existing systems and workflows. Although some companies already employ AI for system integration, its current use remains significantly below what is required. The word “integration” was mentioned 17 times in the interviews, and respondents highlight persistent fragmentation and the need for smoother interoperability. This citation illustrates this perspective:

> If I want to prepare a slide deck, Gemini will give me the outline and the structure, but it will not create the slides for me. If I want to build a prototype, the prototype it generates is very basic and it only gives me the HTML; it will not export anything for me. So there are many limitations. For example, if it actually built the slides, I would use it every day, but it does not. And sometimes writing the outline myself is faster than writing the prompt. These limitations end up preventing me from using it more, but I know new features will come [...] because everything in this market is evolving very quickly. (C02, author’s translation)

Second, the belief that AI will soon be ubiquitous and indispensable underscores the urgency of overcoming the skills gap and lack of AI literacy, since the ability to realize these future benefits depends on developing a workforce capable of understanding, interpreting, and supervising increasingly complex tools.

Finally, the vision of AI-enhanced decision-making, capable of leveraging years of organizational data, hinges on addressing issues of knowledge management and expansion, as effective future applications require systematic documentation, structured data capture, and mechanisms to transform accumulated experience into usable inputs for AI systems.

Together, these relationships show that the anticipated future is not only technologically driven but fundamentally contingent on organizations’ capacity to resolve existing operational, human, and knowledge-related constraints.

5 CONCLUSION

This research investigated how Large Language Models are being incorporated into project management practices, guided by three core research questions that shaped the study from its initial conception to its final analytical synthesis. These questions concerned the main applications of Generative AI and LLMs in project management, the types of benefits generated by these applications in organizational contexts, and the primary challenges companies currently face in implementing AI for project work. Through an extensive literature review and qualitative data collected from interviews with five organizations of diverse sizes and maturity levels, the study demonstrated that the adoption of Generative AI in project environments is gradual, uneven, and deeply influenced by organizational structures, internal capabilities, and socio-technical dynamics that mediate its implementation. Instead of a uniform adoption pattern or a linear progression of technological maturity, the evidence revealed that companies engage with AI in ways that reflect their leadership orientation, governance practices, technical infrastructure, and workforce readiness.

In responding to the first research question, which sought to identify the main applications of AI in project management, the study established that organizations currently deploy LLMs primarily to support automation of operational tasks, communication and collaboration activities, knowledge management and expansion, innovation-related initiatives, training and development, and reporting and documentation. These categories emerged directly from the coding process and represent the most tangible areas where AI tools are producing measurable effects, mentioned by all five companies interviewed. However, the findings also revealed a meaningful divergence between the applications emphasized in academic literature and the uses most common in practice. While theoretical research often highlights advanced areas such as cost management, resource allocation, risk modelling, decision support, and project scheduling optimization, these domains appeared only marginally or not at all in the interviews. This indicates that organizations are still prioritizing low-complexity, high-usability applications, where the benefits are clearer and the risks of misapplication are relatively low. As a result, the theoretical promise of AI-enabled predictive analytics and autonomous optimization in project management remains largely unrealized in current practice.

The second research question concerned the benefits associated with LLM adoption. The analysis revealed nine distinct benefits. Three of these benefits proved to be central and widely shared across all companies: cost and time savings, improved delivery quality, and increased productivity and efficiency. All interviewees consistently observed that LLMs accelerate workflows, reduce manual effort, and enhance the clarity, structure, and precision of deliverables. Additional benefits emerged in more selective patterns, such as improved decision quality, better forecasting, enhanced communication, and more consistent resource utilization. These benefits depended largely on the maturity of internal data practices and on the degree to which AI tools could be contextualized within project routines. A noteworthy contribution of this study is the identification of a benefit not significantly highlighted in prior literature: standardization. The data indicated that companies use LLMs to reduce inconsistency in outputs, improve uniformity across deliverables, and ensure that team members adhere more strictly to organizational conventions or regulations. This emergent code highlights a practical dimension of AI usage that deserves further theoretical exploration, particularly given its potential to reinforce process quality and organizational coherence.

Addressing the third research question, the study identified several challenges that shape and often restrict AI adoption. Some of these challenges were shared by all companies, such as the difficulty of developing qualitative indicators to measure AI benefits, the risk of overreliance on AI tools or inadequate interpretation of outputs, and the persistent skills gap linked to insufficient AI literacy. These findings confirm that organizations face not only technical obstacles but also cognitive and cultural barriers that influence the effectiveness of AI integration. Additional challenges surfaced, including limitations in data quality, concerns about cybersecurity and privacy, insufficient integration with existing systems, resistance to change, and in some cases, limited perceived value of AI tools. An intriguing theoretical insight concerns the absence of the challenge of explainability in all interviews, despite its prominence in academic literature. This absence suggests that, at current maturity levels, practitioners may be more concerned with practical adoption barriers than with epistemic transparency. It may also indicate that explainability will become a more prominent concern only as organizations progress toward more complex and higher-stakes uses of AI.

The theoretical implications of this research derive from both the emergent codes and the theoretical-practice gaps identified. Several codes not widely discussed in academic literature emerged from the empirical data, such as standardization, time to find the solution, limited qualitative indicators, limited value perceived, and integration with existing systems as a central barrier. These findings suggest that current theoretical models may not adequately capture the organizational dynamics and capability-building processes required for AI adoption in project environments. They also highlight the need for future theoretical work that considers AI adoption not only from a technological or methodological standpoint but also from a socio-technical perspective that integrates governance structures, leadership incentives, and internal knowledge-sharing practices. At the same time, the absence of theoretically predicted themes such as advanced analytical applications, autonomous optimization, and explainability issues suggests that the literature may be overestimating the current maturity of AI integration in organizational settings. Future research should therefore investigate the conditions under which organizations transition from early-stage, efficiency-oriented applications toward more strategic and autonomous forms of AI-enabled project management.

The study's practical implications are equally significant. The findings clearly show that organizations seeking to unlock the full benefits of LLMs must invest deliberately in human capabilities, governance mechanisms, and technological integration. AI literacy and training programs are fundamental for ensuring that professionals can critically assess AI outputs, avoid overreliance, and understand the boundaries of automation. Clear and well-communicated governance guidelines are essential for reducing risks related to data privacy, cybersecurity, and ethical usage, especially as companies expand their experimentation with AI tools. Internal platforms and controlled environments contribute substantially to the security and consistency of AI usage, and companies that invest in such infrastructures are better positioned to scale adoption. Integration challenges also have direct managerial relevance, as the lack of integration between AI tools and existing productivity suites limits the continuity and coherence of workflows. Finally, organizations should acknowledge that AI adoption can be a source of competitive advantage, but only when human-AI collaboration is strategically and responsibly structured. This requires managers to embrace hybrid work models that combine critical human judgment with the efficiency and analytical capabilities of AI systems.

Despite offering valuable insights into the current state of AI adoption in project management, this study presents some limitations that should be considered when interpreting its findings. The empirical evidence is based on a small and non-probabilistic sample of five organizations, which restricts the generalizability of the results and reflects only a specific range of organizational maturities, industries, and cultural environments. The research relies on semi-structured interviews, which, although rich in qualitative insight, are subject to self-reporting bias and depend on the interviewees' personal familiarity with AI tools. The study captures a snapshot of AI adoption at a specific point in time, within a rapidly evolving technological landscape in which practices and governance mechanisms are expected to shift significantly. Additionally, as the coding process is exploratory and grounded in inductive reasoning, the prominence or absence of certain themes may reflect characteristics of the sample more than universal patterns of adoption. The study also focuses on perceived uses, benefits, and challenges, without measuring concrete performance indicators or technical metrics related to

AI implementation quality. As a result, the conclusions presented should be interpreted as indicative rather than definitive, and future research should incorporate larger samples, longitudinal perspectives, and objective performance data.

In conclusion, this study shows that LLMs are beginning to influence project management practice in meaningful ways, but their transformative impact remains dependent on a range of organizational, cultural, and technical conditions. Adoption is progressing through incremental and layered stages in which companies prioritize simpler applications and gradually explore more specialized or strategic uses. By mapping applications, benefits, challenges, and the complex relationships among them, the study provides a detailed and empirically grounded understanding of how LLMs currently operate within project environments. The research contributes to theory by identifying emergent codes and by highlighting gaps between theoretical predictions and practical realities. It also offers actionable insights for organizations seeking to adopt AI responsibly and effectively. As AI technologies evolve, project management as a discipline will continue to undergo significant shifts in skills, workflows, and organizational practices. The findings of this thesis underscore the importance of developing not only technological capabilities but also institutional readiness and human-centered strategies that ensure sustainable and high-quality adoption of AI in project work.

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APPENDIX B - INTERVIEW PROTOCOL

Introduction

First of all, thank you very much for agreeing to participate in this interview.

Given the growing use of various types of Artificial Intelligence (AI) across all sectors, and the wide range of tools and use cases, our main goal with this research is to understand the main uses and applications of AI, the most widely adopted models and tools, the challenges faced, and the overall impact on organizations. To explore this topic in greater depth, we are conducting interviews with companies that use AI in project management.

Some important disclaimers: we emphasize that all data will be treated in an aggregated and confidential manner, respecting the principles of research ethics. All information from this interview is protected under a research confidentiality agreement. We will use only the information related to the use of AI in our study. To ensure your comfort, your name and your company's name will be replaced by an identification code.

To better manage information, would you feel comfortable if we record this interview? Again, all material will be protected by the confidentiality agreement, and we are happy to share the full transcript with you afterward.

This interview is divided into two main parts. The first is an open conversation to explore how AI is being used in project management within your company. The second is a hands-on moment to formalize which AI tools you use most frequently and consider most important.

Shall we begin with you telling us a bit about your background and about the company?

General Mapping of AI Use in Project Management

1. How do you define Artificial Intelligence?
2. Do you perceive AI as:
   a. A support tool
   b. A replacement for human functions
   c. A hybrid (support + partial replacement)
3. When and how did the company begin adopting AI in project management?
4. What was the main motivation for adoption (cost reduction, productivity increase, innovation, etc.)?

5. In which project management activities is AI/LLM currently applied?
6. Which AI/LLM techniques and applications does your company use in project management?
7. How does AI complement human work in project management?
8. Can you mention concrete examples of tasks that AI performs that were previously done manually?
9. Has any functionality or model exceeded or failed to meet expectations?
10. Do you integrate these AIs with project management software (MS Project, Jira, Trello, Asana, Monday, etc.)?
11. What are the main benefits observed so far?
12. What are the main challenges in adopting AI in project management?
13. Did any pilot project fail to perform as expected? Why?

Depth and Dynamics of Use

1. How are decisions about AI use in projects made?
2. Could you describe the data your organization uses as input for AI? (Which types of data, internal/external sources, and tools used for data collection?)
3. Is there concern about confidentiality and ethical issues when using external AIs? How is this addressed?Do you use AI models protected from learning from your data?
4. Is there any concern about the robustness of responses and the risk of uncritical or unreviewed use?
5. Is there a protocol for knowledge sharing or AI use among teams?
6. Has AI helped integrate new knowledge that you were previously unaware of?
7. Has AI impacted or accelerated the delivery of innovative products or services? If yes, please explain how.
8. Are there quantitative or qualitative indicators that demonstrate AI's impact on project management? If yes, could you share the results? If not, what is your perception of the outcomes?
9. Has your company adapted processes or structures to integrate AI on a continuous basis? Please explain.
10. Have there been changes in team members' roles or responsibilities?
11. Would you say that AI has helped your company gain a competitive advantage?

Future Perspectives and Closing

1. What are the next steps or plans for expanding the use of AI in project management?
2. What features or improvements would you like to see in the AI tools you currently use?
3. Is there anything I haven't asked that you consider important about this topic?

Hands-on Section

So far, we have gathered excellent insights for the research. To formalize what we have discussed about the use of AI in your company, let's fill out the table below together:

Model	**Has it been used? (Yes/No)**	**Usage Frequency (Daily / Weekly / Occasional)**	**Level of Importance (1 to 5)**	**Main Applications**
GPT (specify model)				
Claude				
Gemini				
Copilot				
Others (specify)				

APPENDIX C - NODES RELATIONSHIPS

Node 1	Relationship type	Node 2
Reporting and documentation	associated	Standardization
Document analysis	associated	Cost and time savings
Cost and time savings	leads to	Increased productivity and efficiency
Faster information access and retrieval	leads to	Increased productivity and efficiency
Increased productivity and efficiency	associated	Improved delivery quality
Innovation	associated	Improved delivery quality
Faster information access and retrieval	associated	Improved delivery quality
Knowledge management and expansion	associated	Faster information access and retrieval
Training and development	associated	Knowledge management and expansion
Risk identification and management	leads to	Risk reduction and better forecasting
Automation of routine tasks	leads to	Increased productivity and efficiency
Automation of routine tasks	leads to	Cost and time savings
Automation of routine tasks	associated	Better resource utilization
Coding	leads to	Cost and time savings
Prioritization	associated	Improved decision quality
Scope definition and clarification	associated	Improved decision quality
Decision-making	associated	Improved decision quality
Monitoring and control	associated	Improved project success rate
Scheduling	associated	Improved project success rate
Improved delivery quality	constrained	Skills gaps and lack of AI literacy
Improved delivery quality	constrained	Overreliance on AI or misinterpretation of outputs
Overreliance on AI or misinterpretation of outputs	associated	Skills gaps and lack of AI literacy
Overreliance on AI or misinterpretation of outputs	associateD	Data availability and quality
Time to find the solution	associated	Limited value perceived
Integration with other systems	associated	Integration with existing systems or workflows
Own platform	associated	Cost of implementation and maintenance
Decision-making	constrained	Data availability and quality
Internal knowledge sharing	reduces	Limited value perceived
Internal knowledge sharing	reduces	Time to find the solution
Internal knowledge sharing	reduces	Skills gaps and lack of AI literacy and lack of AI literacy
Leadership incentive	associated	Governance of AI and guidelines
Leadership incentive	reduces	Resistance to change
Governance of AI and guidelines	associated	Own platform
Leadership incentive	associated	Own platform

Own platform	reduces	Cybersecurity risks and data privacy
Governance of AI and guidelines	reduces	Cybersecurity risks and data privacy
Own platform	facilitates	Knowledge management and expansion
Internal knowledge sharing	associated	Knowledge management and expansion
Future	associated	Integration with existing systems or workflows
Future	associated	Skills gaps and lack of AI literacy
Future	associated	Knowledge management and expansion
Governance of AI and guidelines	associated	Internal knowledge sharing
Leadership incentive	associated	Internal knowledge sharing
Reporting and documentation	associated	Standardization
Document analysis	associated	Cost and time savings
Cost and time savings	leads to	Increased productivity and efficiency
Faster information access and retrieval	leads to	Increased productivity and efficiency
Increased productivity and efficiency	associated	Improved delivery quality
Innovation	associated	Improved delivery quality
Faster information access and retrieval	associated	Improved delivery quality
Knowledge management and expansion	associated	Faster information access and retrieval
Training and development	associated	Knowledge management and expansion
Risk identification and management	leads to	Risk reduction and better forecasting
Automation of routine tasks	leads to	Increased productivity and efficiency
Automation of routine tasks	leads to	Cost and time savings
Automation of routine tasks	associated	Better resource utilization
Coding	leads to	Cost and time savings
Prioritization	associated	Improved decision quality
Scope definition and clarification	associated	Improved decision quality
Decision-making	associated	Improved decision quality