POLITECNICO DI TORINO
MSc in Management Engineering

AI-Enabled and Data-Driven Decision Support Systems for Project Risk Management

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Abstract

Projects are becoming increasingly complex and exposed to multiple sources of uncertainty, making effective risk management essential. At the same time, AI and data-driven technologies are changing the landscape of decision-making across domains. These approaches offer opportunities and challenges for the wider adoption and implementation of predictive and adaptive Project Risk Management (PRM). However, despite the rapid growth of AI applications, their integration into PRM frameworks remains limited and conceptually fragmented.

This thesis conducts a Systematic Literature Review (SLR) to provide an overview of existing AI and data-driven applications for PRM and to identify gaps and opportunities for adoption. Fourteen systematic literature reviews between 2003 and 2025 covering domains such as construction, infrastructure, innovation management and small-medium enterprises were collected from Scopus, in accordance with the PRISMA 2020 guidelines. The studies were then compared, thematically coded and categorized based on PRM phases, AI methods, and contexts.

The results show an uneven but growing interest in AI-enabled PRM. Machine Learning (ML), Natural Language Processing (NLP), Big Data and Internet of Things (IoT), Building Information Modeling (BIM) and Digital Twin (DT) are the most relevant technologies, mainly applied in risk identification, analysis and monitoring. However, lifecycle coverage, interoperability and ethical governance remain underdeveloped.

These findings enable the construction of a multidimensional framework for AI-enabled PRM, which includes technological, processual and contextual dimensions. This framework aims to explain the interplay between smart technologies, risk management processes and organizational facilitators to develop adaptive and transparent decision support systems. The study concludes with a research agenda that seeks to empirically validate and apply the proposed framework across sectors.

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Chapter 1

Introduction

1.1 Context

In the last decade, projects have become increasingly complex due to the involvement of diverse technological, economic and social factors, cross-functional teams and multiple stakeholders. This complexity heightens uncertainty since the ability to anticipate and manage risks is a key factor for project success *(Valadares et al. 2024)*. Disruptive events, ranging from supply chain interruptions to market shifts, are becoming more frequent and severe. Even minor delays in sectors such as construction engineering and large-scale infrastructure can have significant financial and operational repercussions *(Baghalzadeh Shishehgarkhaneh et al. 2024)*.

The PMBOK Guide *(Project Management Institute 2017)* presents Project Risk Management (PRM) as an integrated set of processes designed to ensure the continuous and systematic management of uncertainty. Similarly, ISO 31000 *(International Organization for Standardization 2018)* presents a risk management process applicable at organizational, program and project levels emphasizing principles such as integrated decision-making, dynamic adaptation and continuous improvement.

However, these traditional frameworks are challenged considering the rapidly evolving risk landscape, as highlighted in recent systematic literature reviews. Digital transformation has drastically increased the volume and variety of project data generated by PMIS, BIM, IoT devices and stakeholder communications. This creates opportunities for better decision-making. Yet, traditional PRM processes often lack the capacity to process such data in real time, therefore their predictive and adaptive capabilities are limited *(Salimimoghadam et al. 2025)*.

AI-driven predictive models already demonstrate excellent performance in sectors such as AEC, as they can detect early warnings of delay or cost overruns and outperform traditional forecasting methods *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. Within supply chains, AI-enhanced tools can anticipate disruptions before they cascade across networks, capabilities not achievable through static risk registers *(Baghalzadeh Shishehgarkhaneh et al. 2024)*. Lightweight, cloud-based AI and data-driven solutions can provide SMEs with accessible tools to address risks despite constrained resources *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

Developments of this kind lay the groundwork for exploring the use of AI to enhance PRM, building on the governance structures of PMBOK and ISO 31000. They also help address the practical limitations of data integration by offering real-time responsiveness and predictive analytics *(Prasetyo et al. 2025)*.

1.2 Problem Statement

Despite the strong governance frameworks provided by the PMBOK Guide and ISO 31000, the Project Risk Management (PRM) often struggles to meet the demands of today's fast-paced, data-driven environments. Multiple systematic literature reviews reveal that PRM is predominantly reactive, with organizations frequently addressing risks only after they have materialized *(Rahi, Bourgault & Preece 2022)*. This reactive stance contrasts sharply with the approach identified by PMBOK and ISO 31000, which emphasize the importance of identifying risks early and monitoring them continuously *(International Organization for Standardization 2018; Project Management Institute 2017)*.

A recurring limitation is that PRM processes as well as project data sources do not integrate in real time. In many cases, risk registers that are updated at predefined intervals are static documents forming the basis of traditional PRM. This results in a time lag when it comes to detect emerging risks, which is critical in volatile sectors such as construction and technology *(Baghalzadeh Shishehgarkhaneh et al. 2024)*. For instance, within the construction supply chain, delays in material delivery can have a knock-on effect across multiple firms and project areas. Without timely detection, such risks can escalate quickly, resulting in increased costs and schedule deviation.

Reliance on human judgment poses a major challenge in qualitative risk analysis and this dependency can lead to inconsistency and bias. This is particularly prevalent in small and medium-sized enterprises (SMEs), where data is often not formally collected and assessments are heavily based on individual experience *(Ferreira De Araújo Lima, Crema & Verbano 2020)*. Systematic data collection is often absent, which makes probability-impact evaluations less accurate and limits learning from past projects.

Even in resource-rich sectors, integration barriers exist for quantitative methods. In the AEC industry, AI-powered predictive models using big data can forecast delays and cost overruns more accurately than traditional methods. These models become more accurate when integrated into Building Information Modeling (BIM) systems *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. However, their adoption remains uneven, as many projects still depend on traditional tools despite their limited accuracy.

Research also shows that AI applications focus more on the planning and monitoring/control phases of PRM, while initiation and closing are often neglected *(Adamantiadou & Tsironis 2025)*. This presents significant opportunities for improvement, particularly when AI proactively identifies risks at the project outset and systematically extracts lessons learned at its conclusion.

Adoption barriers extend beyond the technical issues. Organizations and cultures encounter difficulties, including resistance to change, a lack of AI literacy among project managers, and concerns about data privacy and security *(Prasetyo et al. 2025)*. Other studies identify a similar gap between pilot AI implementations and full-scale adoption. Despite promising results, integration costs, interoperability issues and uncertainty over return on investment obstruct this adoption *(Rahi, Bourgault & Preece 2022)*.

These findings together highlight a clear gap between academic research and practical application:

- There is no thorough, process-oriented framework that maps AI and data-driven techniques to specific PRM processes, as defined by PMBOK and ISO 31000.
- Dynamics that are sector-specific influence the AI adoption, including data availability within the AEC sector, the complexity of supply chains, together with the resource constraints affecting SMEs. However, researchers do not explore these dynamics in such a consolidated way.
- The interplay between enabling factors (e.g. leadership support and integration with PMIS) and barriers (e.g. cost, skills shortages and cultural resistance) has yet to be synthesized systematically.

These gaps must be addressed to move from what is a reactive, static PRM model to a predictive, adaptive one that is continuously integrated with real-time project environments. This thesis responds to this need by systematically reviewing the existing literature to identify how AI can improve PRM.

1.3 Research Objectives and Questions

The aim of this thesis is to conduct a systematic review of the literature and integrate Artificial Intelligence (AI) into Project Risk Management (PRM), emphasizing applications that align with PMBOK and ISO 31000 processes.

Specific objectives:

- *O1:* Identify AI and data-driven applications across PRM phases.
- *O2:* Compare AI-enabled PRM practices across sectors.
- *O3:* Investigate enablers and barriers to AI adoption in PRM.
- *O4:* Explore AI integration within PRM frameworks.

Research questions:

- *RQ1:* Which AI and data-driven techniques are currently used in PRM? Which PRM phases do these techniques target?
- *RQ2:* Which sectors have demonstrated the most advanced PRM practices enabled by AI?
- *RQ3:* What enables or prevents organizations from adopting AI in PRM?
- *RQ4:* What AI integration gaps exist in PMBOK processes? What gaps remain for AI integration into ISO 31000 processes?

Expected contribution:

- Map AI and data-driven applications within PRM frameworks in a consolidated, process-oriented way.
- To select AI solutions, practitioners need sector-specific insights that provide clear direction.
- Identify both theoretical and practical gaps to inform future academic research.

1.4 Thesis Structure

The thesis is organized as follows:

- *Chapter 2:* reviews the theoretical foundations of PRM, presenting PMBOK and ISO 31000 processes, traditional methods, limitations and the evolution towards AI-improved approaches.
- *Chapter 3:* details the methodology for the systematic literature review, covering database selection, search strategy, inclusion and exclusion criteria, and thematic synthesis used to extract and structure evidence.

- *Chapter 4:* presents the results of the review, mapping how AI and data-driven techniques are applied across PRM phases. It compares findings from the fourteen selected SLRs, identifies the contexts of application, and analyzes common enablers, barriers and research gaps.
- *Chapter 5:* develops a conceptual and multi-layered framework integrating technological, processual and contextual dimensions of AI-enabled PRM. It discusses the framework's theoretical and practical implications, providing both an interpretive model and an implementation roadmap for organizations.
- *Chapter 6:* concludes the thesis by summarizing the main findings, highlighting study limitations and proposing future research directions aimed at validating and extending the proposed framework.

Chapter 2

Theoretical Foundations and Methodological Background

2.1 Defining the Scope of Project Risk Management

Project Risk Management (PRM) is a structured, systematic method that identifies, analyzes, responds to and monitors risks that could affect the achievement of specific project goals. The PMBOK Guide defines risk as "an uncertain event or condition that, if it occurs, has a positive or negative effect on a project objective". *(Project Management Institute 2017).* Similarly, the ISO 31000 standard states that risk affects objectives and presents risk management as continuous and organization-wide, rather than functioning as a discrete project *(International Organization for Standardization 2018).*

The scope of PRM extends beyond threat mitigation and also includes identifying opportunities for better project performance. Adopting this dual perspective to manage both positive and negative risks ensures that risk management creates value instead of simply avoiding loss. Both the PMBOK and ISO frameworks define PRM as an iterative process that is integrated into each stage of the project lifecycle, that ranges from its initiation to its closure and is applied across all governance levels.

From a methodological perspective, PRM falls within two main categories of technique:

- *Qualitative methods*: include checklists, interviews, brainstorming sessions, SWOT analysis and expert judgments. Usually, they are faster to use and work well in the initial phase of reviews when facts are sparse.
- *Quantitative methods*: measure risk exposure including potential impacts through advanced analytical approaches, such as sensitivity analysis, decision tree analysis and Monte Carlo simulations. While these methods can provide valuable insights, they rely heavily on accurate,

structured and timely data, something not always available, particularly when organizations have limited resources *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

PRM is also cross-functional in an intrinsic way. The PMBOK clearly links it to knowledge areas such as scheduling, costing, quality and procurement management. For example, a risk event that affects a critical supplier has not only a procurement implication but can also impact schedule, cost and quality. ISO 31000 reinforces this linked view, since it positions risk management as a decision-making enabler, ensuring that uncertainty is consistently embedded in decision-making processes.

Although these theoretical definitions appear clear, the way in which both sectors and organizations practically implement them can vary widely. In many cases, risk management is treated merely as a compliance requirement, which has limited influence on day-to-day decisions *(Rahi, Bourgault & Preece 2022)*. For instance, in complex supply chains, risk processes often fail to capture emerging vulnerabilities and obstruct any timely disruption prevention *(Baghalzadeh Shishehgarkhaneh et al. 2024)*. Similarly, within the AEC sector, although the industry generates massive amounts of project data via BIM, IoT devices and PMIS platforms, traditional PRM methods cannot effectively analyze all this information instantly *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*.

The pace of change in modern project environments is accelerating, further complicating the alignment between field execution and the intended project framework. Globalization has increased the reliance of projects on stakeholders because digital change has revealed new forms of risk, such as cyberattacks, data integrity flaws and the rapid obsolescence of current PRM methods *(Salimimoghadam et al. 2025)*. In response, more advanced, AI-enabled data-driven tools are helping PRM toward improving its predictive, adaptive and analytical capabilities.

Since AI recognizes this foundation, examining how PRM is operationalized within established project management standards is important. The PMBOK Guide is useful for managing risk within individual projects, since it includes process-oriented and detailed approaches.

2.2 PRM According to the PMBOK Guide

The PMBOK Guide *(Project Management Institute 2017)* presents Project Risk Management as a series of seven interrelated processes: Plan Risk Management, Identify Risks, Perform Qualitative Risk Analysis, Perform Quantitative Risk Analysis, Plan Risk Responses, Implement Risk Responses and Monitor Risks. These processes are designed to be iterative and cyclical, with outputs from one process feeding into the others as the project evolves.

Plan Risk Management: establishes the foundation for all risk activities and defines how these activities will be conducted. It defines roles and responsibilities and determines stakeholder risk appetite. It also sets the budget and schedule for risk-related activities, specifying the tools and techniques to be used. Without this step, risk management tends to become fragmented and inconsistent, reducing its effectiveness.

Identify Risks: has a focus on systematically determining and document the characteristics of all the risks that may affect the project. This process relies on method such as brainstorming, document review and SWOT analysis, as well as expert interviews. Importantly, risk identification is an ongoing process. To then capture new risks that emerge as the project progresses, it must be repeated regularly.

Perform Qualitative Risk Analysis: evaluates the impact and probability of each identified risk, often using similar prioritization tools or a probability-impact matrix. While this helps to focus attention on the most important threats and opportunities, the process is inherently subjective as it relies heavily on the experience and judgment of those involved *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

Perform Quantitative Risk Analysis: involves numerically estimating of the overall effect that risks have on project objectives. Data-driven insights into risk exposure are provided using techniques such as Monte Carlo simulation, while contingency planning can be informed by decision tree analysis and sensitivity analysis. However, these methods require accurate, complete and timely data, which is not always readily available in practice *(Baghalzadeh Shishehgarkhaneh et al. 2024)*.

Plan Risk Responses: develops specific strategies for high-priority risks. Strategies may include avoidance, mitigation, transfer, or acceptance for threats they address, and they may involve exploiting, improving, or sharing for opportunities they pursue. As demonstrated, AI-enabled scenario modeling improves this process. Before resources are committed, project teams simulate various responses and assess their potential effectiveness *(Adamantiadou & Tsironis 2025)*.

Implement Risk Response: executes the mitigation, transfer, avoidance or acceptance actions defined during planning. This process ensures that response strategies are carried out as intended by coordinating resources, updating project documents and informing stakeholders. Because project conditions evolve, timely implementation is essential; delays or weak execution can limit the effectiveness of even well-designed risk responses.

Monitor Risks: ensures that risk management continues uninterrupted and involves tracking risks, identifying new risks, reassessing existing ones and evaluating the performance of risk responses. However, in practice, monitoring is often reduced to periodic reporting, which can fail to capture emerging risks in fast-changing project environments.

Figure 2.1: PRM processes according to PMBOK

Although PMBOK offers a broad and well-known framework, it does not mandate technologies for complex analytics or for live monitoring. Integrating AI-based tools into PMBOK processes can increase responsiveness, predictive ability and overall effectiveness, while maintaining governance principles intact.

2.3 PRM According to ISO 31000

The ISO 31000 standard *(International Organization for Standardization 2018)* provides a universally applicable framework for risk management, that is designed to operate across corporate, program and project levels. Unlike the PMBOK Guide, which specifically focuses on risk management processes at the project level, ISO 31000 offers a broader governance-oriented approach that positions risk management as crucial for organizational decision-making and performance improvement.

According to ISO 31000, risk is defined as "the effect of uncertainty on objectives", and it is clearly noted that this effect can be positive or negative. The framework uses guiding principles that comprehensively structure an approach, customize to context, include dynamism, use the best information available and consider human and cultural factors, plus commit to constant improvement. These principles are embedded into the culture and governance of the organization to ensure risk management adds value.

ISO 31000 outlines a risk management process consisting of each of the following key stages:

- *Scope, Context, Criteria*: defines what is included in the risk assessment, understand the internal and external environment, and establish the criteria used to evaluate risks.
- *Risk Assessment*: is a three-part process comprising risk identification, risk analysis and risk evaluation. Risk identification seeks to capture all relevant uncertainties, while risk analysis estimates what is likely to happen and the consequences. Risk evaluation weighs these results against set criteria to identify risks requiring treatment.
- *Risk Treatment*: involves selecting and implementing measures to modify risk, which may involve avoidance, reduction, sharing or acceptance. ISO 31000 emphasizes cost-effective measures that are aligned with organizational risk appetite and adaptable.
- *Monitoring and Review*: continuously tracks risk and the effectiveness of treatments, and adjusts as conditions evolve.
- *Communication and Consultation*: engages stakeholders at every stage to ensure that perceptions of risk are understood and addressed.
- *Recording and Reporting*: ensures that risk information, decisions, and outcomes are systematically documented and communicated clearly to support transparency and continuous improvement.

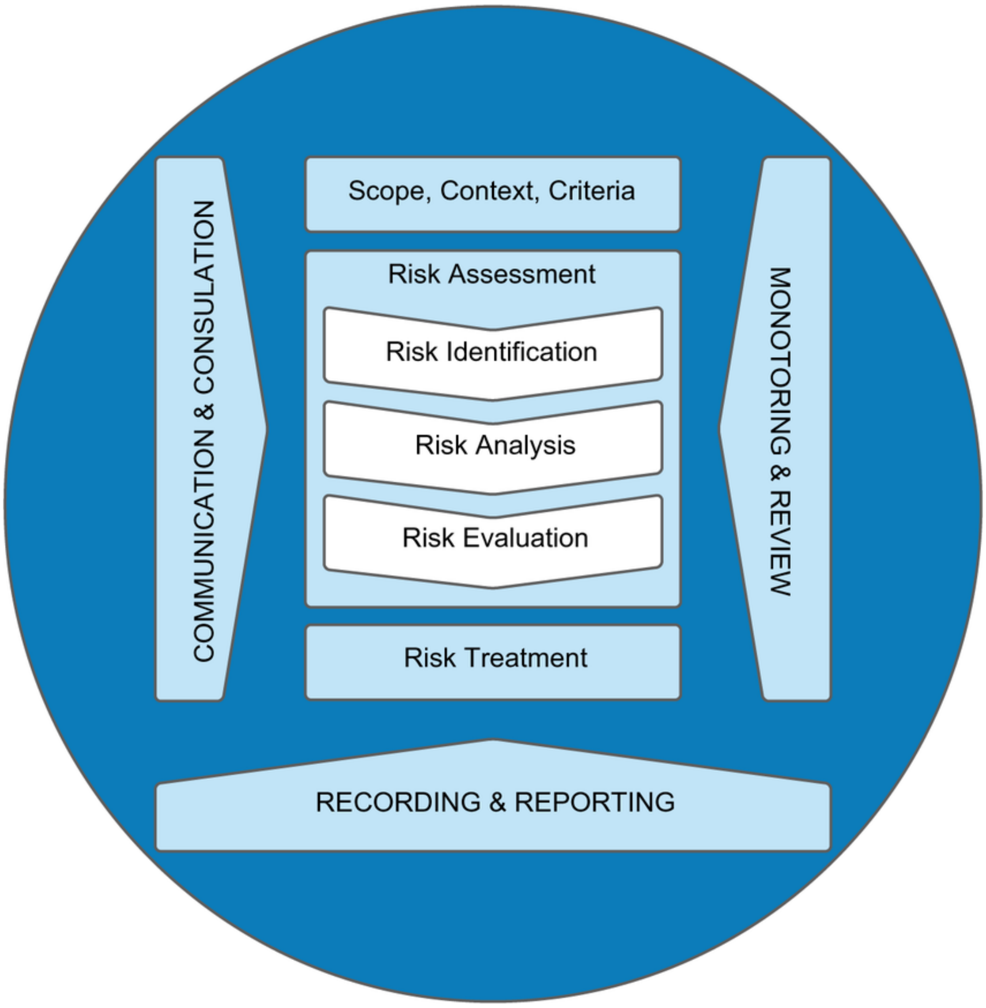

Figure 2.2: PRM processes according to ISO 31000

ISO 31000 places a strong emphasis on integration. This is one of the standard's defining strength, which states that risk management should be embedded within all organizational activities, including governance, strategy and operational processes. This makes it particularly relevant for organizations seeking to align project-level risk management with enterprise risk management systems. However, its broad scope can limit consistency at the project level compared with the more prescriptive structure of PMBOK.

The "dynamic" principle of ISO 31000 is especially relevant in today's volatile project environments. Predictive AI models can support this principle by detecting deviations from key performance indicators (KPIs) using BIM and IoT data streams *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. In SMEs, for instance, lightweight AI tools can improve the use of available information by aggregating and analyzing small datasets *(Ferreira De Araújo Lima, Crema & Verbano 2020)*. Similarly, in open innovation projects, AI-driven text analytics can enhance stakeholder consultation by systematically analyzing perceptions and communications *(Prasetyo et al. 2025)*.

In summary, ISO 31000 provides a flexible, principle-based framework for risk management that can be adapted to suit a variety of corporate settings. PMBOK offers detailed process guidance on projects processes, while ISO ensures the embedding of these processes within a broader organizational risk culture. The two frameworks are therefore complementary: PMBOK takes a rigorous approach, while ISO takes a tactical approach. AI technologies can be integrated into the ISO framework, enabling principles such as dynamism, inclusiveness and the use of the best available information to be operationalized in data-rich project environments.

2.4 Traditional PRM Methods

Traditional Project Risk Management (PRM) methods, as outlined in the PMBOK Guide and ISO 31000, provide a systematic approach to handling uncertainty through a structured sequence of steps. This process typically involves defining a risk management plan, identifying risks, analyzing their probability and impact, developing mitigation or response strategies and monitoring risks throughout the project lifecycle. However, their effectiveness in practice depends on selected tools and techniques, data quality and organizational expertise.

Qualitative methods typically used in PRM include brainstorming sessions, expert judgment, structured interviews, risk checklists and SWOT analyses. These approaches are valued for their accessibility, speed, relatively low cost and are particularly useful in the early stages of projects. In fact, the initial direction comes from the perceptions of experienced professionals when thorough data may be unavailable. However, qualitative methods are also criticized because of their subjectivity *(Ferreira De Araújo Lima, Crema & Verbano 2020).*

Risks and their potential impact on project objectives are numerically modeled using quantitative methods to provide a more objective basis for decision-making. Techniques such as Earned Value Management (EVM), sensitivity analysis, decision tree analysis and Monte Carlo simulation are well documented in academic literature and in professional practice. These methods help project managers to model the impact of different risk scenarios and determine the appropriate contingency reserves by estimating Expected Monetary Value (EMV). However, it should be noted that quantitative methods can often be resource intensive and require substantial volumes of reliable and current data.

Risk registers, which serve as central repositories for identified risks and their characteristics, as well as planned responses, are another key feature of traditional PRM. They are intended to evolve throughout the project as they are continuously updated with new risks and changes to existing ones.

However, risk registers can often be static in practice, being updated only during scheduled reviews or at periodic intervals. This weakens the effectiveness of risk management responses and can cause critical issues to be detected late, particularly in volatile environments *(Rahi, Bourgault & Preece 2022)*.

Whether in theory or practice, PRM methods align with organizational governance frameworks in a different way. While ISO 31000 emphasizes the integration of risk management into all governance and decision-making levels, the PMBOK positions PRM as a project-specific knowledge area that must be connected to scope, schedule and cost management. The analyzed studies show that PRM is often isolated within organizations, despite this alignment being theoretical. Consequently, its integration into broader project management processes is still insufficient. *(Adamantiadou & Tsironis 2025)*.

Finally, the context-specific evidence illustrates how the traditional PRM methods can be both effective and ineffective, depending on the conditions in which they are applied. Within the AEC industry, traditional quantitative forecasting tools are still widely used. However, AI-driven predictive models are increasingly outperforming them when applied to project delays and cost overruns *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. Moreover, traditional approaches often fail to anticipate cascading effects across multiple tiers of the supply chain management, which can result in systemic vulnerabilities *(Baghalzadeh Shishehgarkhaneh et al. 2024)*. Similarly, PRM for SMEs is often underdeveloped or inconsistent; methods tend to be simplified to match limited resources, resulting in gaps in risk identification and analysis.

In summary, traditional PRM methods, based on PMBOK and ISO 31000, provide the necessary structure for systematically addressing project risks. However, they rely on qualitative judgments, so quantitative models require data and tools, such as risk registers, which remain static. Therefore, their effectiveness is limited in dynamic, data-intensive project environments. The consistent highlighting of these weaknesses within contexts and throughout studies underscores the need for improvements to risk management approaches that enable technology to evolve more closely with artificial intelligence.

2.5 Limitations of Traditional PRM

Although traditional Project Risk Management (PRM) methods such as those outlined in the PMBOK Guide and ISO 31000 provide a solid foundation, their practical application reveals ongoing issues that obstruct their effectiveness in current project settings. These weaknesses are not isolated but systemic, cutting across methodologies, contexts and organizational sizes. Both theoretical standards and empirical literature have repeatedly highlighted them.

One major limitation is the largely reactive nature of traditional PRM. Organizations often use PRM to respond to problems only after their occurrence instead of anticipating them *(Rahi, Bourgault & Preece 2022)*. In practice, however, both PMBOK and ISO emphasize the early identification and continuous monitoring of risks. Risk registers are designed to evolve during the project lifecycle, but they frequently become static documents that are updated at fixed review intervals. In dynamic environments, such as construction or technology projects, this lag can result in critical risks being overlooked until they materialize, thereby weakening the very purpose of risk management.

The dependence on subjective judgments in qualitative methods presents a second challenge. Tools such as expert interviews, probability-impact matrices and brainstorming rely heavily on stakeholders' knowledge and perspectives. While valuable, this approach is biased inconsistent and causes over reliance on individual experience. In smaller organizations where data availability is limited and resources are constrained, qualitative analysis dominates. This makes risk assessments highly variable and sometimes unreliable *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

A third limitation is that quantitative methods require a lot of data. High-quality structured data can support powerful insights from Monte Carlo simulations, decision tree analysis and EVM. However, real data is often sparse, inaccurate or outdated in projects. Incomplete information often reduces the predictive accuracy of models within multi-tiered supply chains, making organizations vulnerable to cascading disruptions *(Baghalzadeh Shishehgarkhaneh et al. 2024)*. Similarly, BIM and IoT generate huge amount of data in the AEC industry, but traditional PRM methods cannot process it instantly *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*.

A fourth weakness is that PRM is implemented only in isolated areas. Despite the insistence of ISO 31000, risk activities are often isolated from other project management functions, even though risk management should be integrated into all governance structures and decision-making processes. Moreover, risk management phases are often disconnected from operational systems such as PMIS or ERP, so organizations cannot link risk assessments to real-time project performance data. As result, outputs lose relevance for planned decision-making *(Adamantiadou & Tsironis 2025)*.

Finally, these methodological limitations are worsened by cultural and organizational barriers. For example, project managers who resist to change, display low risk awareness, or receive insufficient training, reduce the impact of even well-designed PRM processes *(Prasetyo et al. 2025)*. In larger organizations, the challenge often lies in aligning project-level risk management with enterprise-level governance structures, just as recommended by ISO 31000. When aligned, risk processes contribute to overall resilience, despite remaining fragmented.

Taken together, the above limitations highlight a fundamental gap. This gap lies between the prescriptive frameworks of PMBOK and ISO, and the practical realities of project execution. Traditional PRM provides principles that govern structured processes, but it cannot handle the volume, complexity and speed of current projects. Moreover, the literature consistently highlights the need for improved methods to enhance PRM predictive, adaptive and integrative functions. This gap enables us to explore the use of AI to augment customary frameworks, as it transforms risk management from just a reactive and fragmented activity into a proactive, data-driven and continuous process.

2.6 The Evolution Toward AI-Enabled PRM

The limitations of traditional PRM have become more apparent in project settings that are characterized by Volatility, Uncertainty, Complexity, and Ambiguity (VUCA). Globalization and digital transformation, along with the growing interdependence of supply chains, are creating a risk landscape that is evolving faster than processes can effectively manage. In this setting, both qualitative and quantitative methods struggle to predict and adapt sufficiently to ensure project resilience *(Rahi, Bourgault & Preece 2022)*.

Digital transformation has emerged and altered conditions radically. PRM now operates in all these environments, which generate huge quantities of data from diverse sources such as PMIS, BIM, IoT devices and collaborative platforms. While these data streams could improve risk awareness and decision-making, the PRM methods designed by PMBOK and ISO 31000 are not intended for integrating, processing and analyzing such volumes in real time *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. So, project teams cannot exploit information to proactively manage risk due to the widening gap.

Thanks to the current context, PRM has seen a significant increase in the integration of AI and data-driven technologies, which can process large amounts of data and identify patterns. They range from machine learning and natural language processing to predictive analytics and optimization algorithms, which generate actionable insights with a speed and accuracy beyond human capability. Several systematic literature reviews suggest that AI and data-driven methodologies do not replace existing frameworks such as PMBOK and ISO 31000, but instead enable and improve the application

(Adamantiadou & Tsironis 2025).

AI-driven predictive models demonstrate significantly higher performance in AEC projects. These models can detect early warning signs of schedule delays and cost overruns weeks before they occur, allowing them to outperform conventional forecasting tools *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023).* In addition, AI-based risk detection systems can identify vulnerabilities and anticipate cascading disruptions across multiple supply chain tiers before they materialize *(Baghalzadeh Shishehgarkhaneh et al. 2024).* For SMEs, lightweight cloud-based AI and data-driven solutions provide an opportunity to overcome resource constraints by automating risk identification and monitoring. *(Ferreira De Araújo Lima, Crema & Verbano 2020).*

Building on this evidence, AI enables novel capabilities within PRM, as evidenced in the literature. Natural language processing can improve risk identification by analyzing large amounts of unstructured data, such as project reports, contracts and stakeholder communications *(Prasetyo et al. 2025).* Machine learning algorithms can refine probability-impact assessments over time by learning from the historical project data, thereby reducing the intrinsic subjectivity of traditional qualitative methods. Furthermore, AI-enabled scenario modeling allows project managers to test alternative risk responses dynamically, improving the quality of decisions during the planning and monitoring phases *(Adamantiadou & Tsironis 2025).*

Despite systematic literature reviews showing that AI integration into PRM remains fragmented and uneven, these are promising development. While most applications appear during the planning and monitoring phases, the initiation and closing ones are less explored. In addition, organizations encounter difficulties, such as staff resistance to change, project managers lacking AI literacy and concerns about data privacy and governance, all of which limit adoption.

In summary, AI-enhanced, data-driven PRM has evolved from static, reactive approaches to proactive, predictive and adaptive methods. AI offers the potential for operationalizing the principles within PMBOK and ISO 31000 in a dynamic way. Rather than replacing governance structure, AI can make risk management much more responsive to the demands of complex, data-rich environments. This thesis builds on this perspective to map how AI is currently applied across PRM processes identifying enablers, barriers and gaps that must be addressed for AI to reach its full potential.

Chapter 3

Methodology: Systematic Literature Review (SLR)

3.1 Introduction

A Systematic Literature Review (SLR) is a rigorous methodology for synthesizing existing research in a transparent and reproducible way that is also methodologically solid. Unlike traditional narrative reviews, which often reflect the researcher's subjective preferences or selective readings, SLRs are guided by explicit protocols that maximize coverage and minimize bias. Evidence-based research is based on them and this is widely recognized across disciplines *(Kitchenham & Charters 2007)*.

The SLR methodology originated in the medical sciences in the late 1900s with the evidence-based medicine movement, when researchers sought structured methods to synthesize numerous clinical trials. Over time, this methodology spread to the social sciences, education and business, as well as engineering, because it was versatile and valuable in consolidating fragmented knowledge. The SLR approach is becoming increasingly relevant in project management, where empirical studies often rely on diverse methodologies and are scattered across industries such as construction, IT and healthcare.

SLRs have two main functions. Firstly, they provide a comprehensive overview of the state of the art by highlighting patterns, contradictions and dominant themes. Secondly, they help scholars to identify research gaps and lay the foundation for future investigations. In fact, systematic literature reviews are not merely descriptive, they also ensure that research synthesis remains evidence-based, transparent and critical, as outlined in PRISMA initial statement *(Moher et al. 2009)*.

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) *(Moher et al. 2009)* framework is now the standard guideline for designing and reporting systematic reviews.

Using it, researchers must document their process in detail, from the research questions to the article selection and exclusion. Moreover, a PRISMA flow diagram is essential. It graphically illustrates the number of studies that were identified, screened, excluded and included. This level of transparency reinforces the credibility of the review and allows researchers to build on the study later *(Page et al. 2021)*.

The exclusive use of SLRs is particularly appropriate in the context of this thesis, as it offers the most rigorous approach for consolidating existing perspectives and positioning them within established frameworks such as PMBOK and ISO 31000. Moreover, this method helps identify both the opportunities and the gaps that remain in the current body of knowledge.

3.2 The Role of Systematic Literature Reviews in Project Management

Systematic literature reviews have become increasingly important in project management research, as the traditional boundaries of the discipline are no longer its outer limits. Early project management studies often focused on single industries, such as construction or engineering, or were limited to large infrastructure projects. While this approach was useful, it resulted in fragmented knowledge, making it difficult to develop general theories or practices.

Over the past decade, important changes in project management have been driven by globalization, digitalization and have increased project complexity. Risks now include dynamic threats such as supply chain disruptions, cybersecurity breaches and rapidly shifting stakeholder expectations, which are no longer confined to cost overruns or schedule delays. In such a context, synthesizing knowledge from diverse sources becomes essential. SLRs can bridge disciplinary gaps by capturing perceptions from engineering, management science, IT, innovation studies and consolidating them into coherent themes.

Systematic literature reviews in risk management have been applied to topics such as:

- Construction supply chain, where reviews show that disruptions can spread through *(Baghalzadeh Shishehgarkhaneh et al. 2024)*.
- SME risk practices, where studies underline that smaller firms often lack resources, demonstrating that lightweight, affordable tools are essential *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

- Digital transformation, which influences project planning monitoring and control, as SLRs reveal how big data and AI and data-driven techniques are adopted in project management (*Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023*; *Salimimoghadam et al. 2025*).

These examples demonstrate that SLRs are repositories of accumulated knowledge and function as structured tools for identifying gaps between theory and practice. For instance, while many organizations still manage risks through static registers and subjective assessments, SLRs reveal that ISO 31000 emphasizes principles such as dynamism and integration. Similarly, although PMBOK provides explicit guidance on risk management, the examined studies show that many contexts, particularly SMEs, do not often use these processes.

In this thesis, a systematic literature review was conducted in accordance with PRISMA guidelines to ensure transparency and methodological rigor. The following sections outline the search strategy, screening procedures, and synthesis approach, and present the main findings of the review.

3.3 Research Design

This thesis adopts a Systematic Literature Review (SLR) methodology to investigate the integration of Artificial Intelligence (AI) into Project Risk Management (PRM). This approach was deemed the most appropriate approach given the interdisciplinary nature of the topic. PRM, in fact, is typically studied within management frameworks, whereas AI applications tend to be found in technical fields such as computer science, engineering, and data science. This requires a structured and transparent approach to gathering, filtering and synthesizing knowledge.

The design of the systematic literature review follows the PRISMA statement (*Moher et al. 2009*; *Page et al. 2021*). that provides guidelines and a flow diagram to ensure transparency in reporting, helping other scholars to replicate or extend the review.

The guiding research questions *(RQs)* are:

- *RQ1:* Which AI and data-driven techniques are currently used in PRM? Which PRM phases do these techniques target?
- *RQ2:* Which sectors have demonstrated the most advanced PRM practices enabled by AI?
- *RQ3:* What enables or prevents organizations from adopting AI in PRM?
- *RQ4:* What AI integration gaps exist in PMBOK processes? What gaps remain for AI integration into ISO 31000 processes?

3.4 Search Strategy

The review used Scopus as the primary database because it provides extensive coverage of peer-reviewed journals and conference proceedings in management and technical disciplines. Scopus is widely regarded as an extremely comprehensive source for SLR in PRM, making it an appropriate source for this study.

The search query applied was intentionally precise to capture reviews that explicitly addressed the subject of interest:

TITLE-ABS-KEY((“systematic literature review” OR “systematic review” OR “literature review”) AND (“project risk management” OR “project risk” OR “risk management”))

At the initial stage, the search was conducted without restrictions regarding publication year, but only studies published in English in peer-reviewed journals or conference proceedings were considered eligible. This decision was made to ensure that the review focused on high-quality and internationally accessible research.

This rationale targets systematic literature reviews rather than individual case studies. The reasons for this approach are two. Firstly, systematic literature reviews have already applied strict and transparent protocols for identifying and synthesizing primary research. This strengthens the reliability of the conclusions within those reviews. Secondly, AI applications are developing rapidly in project management, so we can build on existing reviews to establish a robust foundation and avoid the duplication of work during empirical screening. Therefore, this thesis positions itself as a thorough synthesis of systematic evidence, providing a higher-level perspective that compares, integrates and then interprets the results of prior reviews considering PRM frameworks.

3.5 Inclusion and Exclusion Criteria

To ensure methodological rigor and transparency, explicit inclusion and exclusion criteria were established in accordance with PRISMA guidelines prior to the screening process.

Inclusion criteria:

- Articles that explicitly adopt a systematic literature review or structured review methodology.
- Studies focusing on project management or project risk management.

- Publications addressing PRM in relation to AI or data-driven techniques.
- Conference proceedings published in peer-reviewed journal articles.
- Publications written in English.

Exclusion criteria:

- Grey literature including reports, editorials, dissertations, narrative reviews, conceptual papers and opinion pieces.
- Studies addressing enterprise risk management without a project-level perspective.
- Publications in which risk management is mentioned only marginally and is not the central focus.
- Sources not written in English or not peer reviewed.
- Articles for which the full text was not available despite reasonable retrieval attempts.

These criteria ensured that the selected corpus of studies was both reliable and directly relevant to the objectives of the thesis.

3.6 Screening and Selection Process

The initial query in Scopus retrieved a total of 759 articles, then the screening process was conducted in three main stages:

1. Duplicate removal: No duplicate records were detected.
2. Title and abstract screening: 628 studies were excluded at this stage because they did not focus on PRM, were not systematic literature review or lacked reference to AI and digital tools. This step reduced the corpus to 131 articles.
3. Full-text retrieval and review: Of the 131 records, 44 full texts could not be retrieved, despite reasonable attempts through institutional access and open sources. The remaining articles were then examined in depth using the inclusion and exclusion criteria, resulting in the exclusion of an additional 73 studies.

The main body of evidence for this thesis is drawn from a final set of 14 studies that remained after the full screening process.

The PRISMA flow diagram *(Figure 3.1)* summarizes all the entire approach, depicting the number of records that were identified, screened, excluded and included. This ensures full transparency and replicability of the selection procedure.

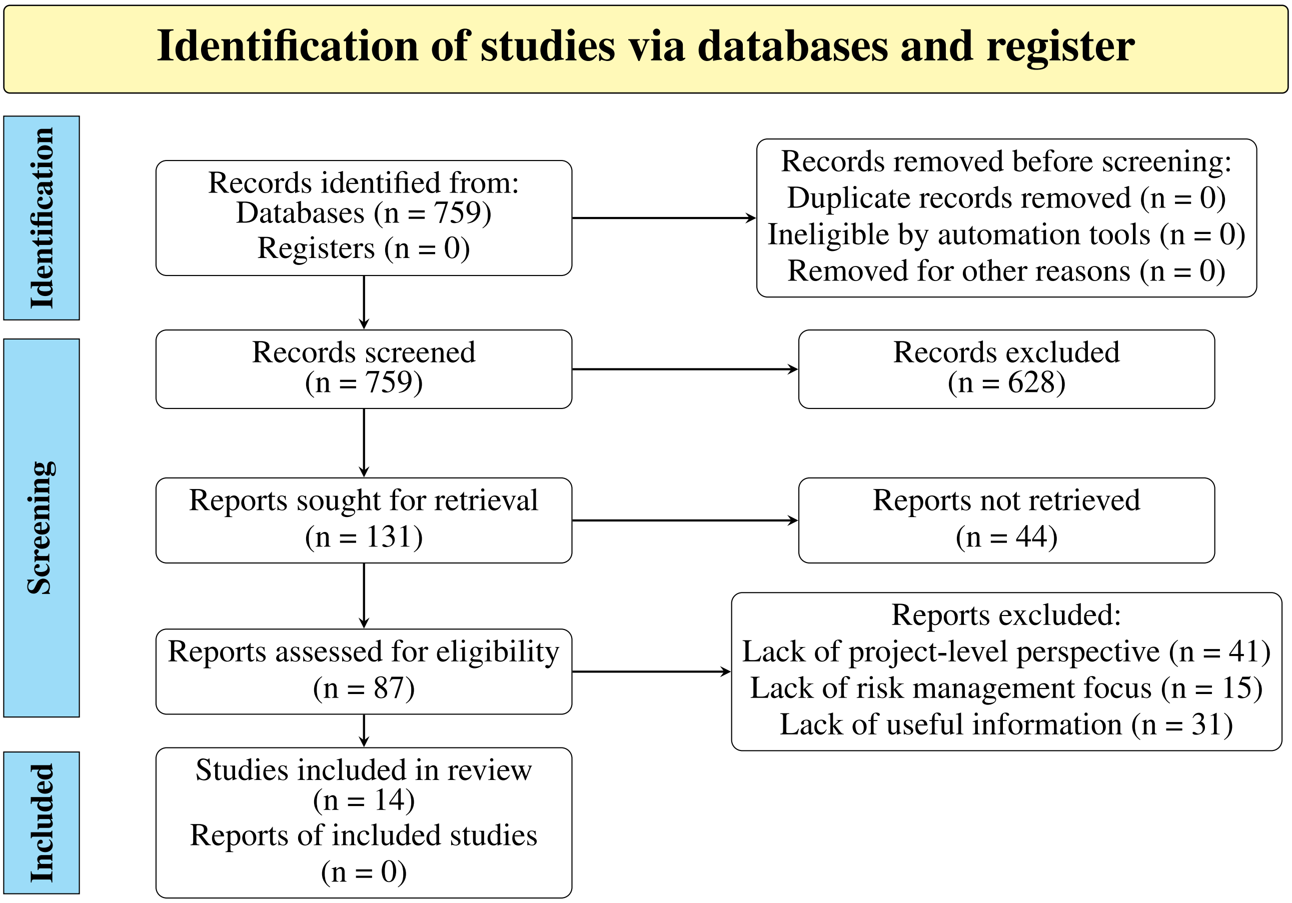

Figure 3.1: PRISMA Flow Diagram

3.7 Data Extraction and Synthesis

For the 14 systematic literature reviews included in the final corpus, more structured data were extracted. This was done to ensure that, despite their different scopes and approaches, the studies were comparable.

For each review, the following key aspects were recorded:

- Bibliographic information (author, year, outlet).
- The sector or context of application.
- The AI or digital techniques discussed.
- The PRM processes addressed.
- The main findings, including reported benefits, enablers, barriers and gaps.

To synthesize the evidence, the reviews were analyzed thematically. In this analysis, findings were grouped according to PRM processes and context focus. Using this approach, several recurring patterns were identified including strong AI adoption in the construction sector, limited use among SMEs and a predominant focus on risk analysis and monitoring were identified. Research gaps aslo emerged such as limited attention to initiation and closure phases, persistent BIM and DT incompatibility issues and a lack of cross-context comparative studies.

3.8 Findings from the Systematic Literature Review

The final set of 14 systematic literature reviews, published between 2003 and 2025, provides an integrated overview of the use of Artificial Intelligence (AI) and digital technologies in Project Risk Management (PRM). The results can be grouped using descriptive publication trends, thematic focus on techniques and processes, methodological approaches, as well as common research gaps.

3.8.1 Descriptive Trends

The body of the evidence shows a significant increase in publications over the last decade due to the growing importance of digitalization in project management. From 2022 onwards, the number of systematic literature reviews increased significantly, especially in the AEC sector, with BIM, IoT and Digital Twin technologies playing a central role in digital transformation. Other, broader reviews focus on supply chains, SMEs, innovation projects and global systemic risks. This demonstrates that PRM research has become increasingly various. However, a sectoral bias toward construction and infrastructure remains apparent.

3.8.2 Topic Trends

The reviews highlight several AI-enabled and data-driven PRM methods:

- Machine learning (ML) and big data analytics improve forecasting of delays, cost overruns and risk scenarios.
- Natural Language Processing (NLP) helps to identify systematic risks through the analysis of contracts, reports and patents.
- Uncertainty modeling can be supported by fuzzy logic and simulation, especially regarding global cost risk factors and supply chains.
- In the construction sector, BIM and Digital Twin are widely discussed since they enable real-time monitoring, safety analysis and better decision support for project managers.

When mapped to PRM processes, as defined in PMBOK and ISO 31000, most applications are concentrated in risk identification, analysis and monitoring. While some studies support risk response through scenario modeling and optimization, risk planning and closure phases are only marginally addressed. For example, research on PPPs tends to focus on risk allocation at the initiation stage and BIM-based studies often discuss lessons learned primarily in renovation projects.

3.8.3 Methodological Trends

All the fourteen studies examined adopted structured protocols, with most explicitly following the PRISMA statement. Thematic coding, bibliometric mapping and hybrid approaches offer different methodologies, but they all aim to ensure transparency in the search and screening processes. However, the synthesis revealed a terminological divide. Management-oriented reviews emphasize concepts such as governance and resilience, whereas technical reviews focusing on BIM and DT concentrate more on interoperability, standards and schema limitations. This divergence shows the difficulty of integrating perceptions across such domains, yet it also confirms the truly interdisciplinary nature of AI within PRM.

3.8.4 Gaps in the Literature

Despite growing interest, all the reviews consistently underline several limitations:

- AI applications are primarily used for planning, identification and monitoring. Given this lifecycle imbalance, initiation and closure remain underdeveloped.
- AEC industry dominate, while sectors such as IT, healthcare and public administration are scarcely represented.
- Smaller firms face cost, skills and resources barriers. However, AI solutions are rarely adapted to meet the needs of all SMEs.
- BIM and DT reviews highlight technical barriers, particularly the lack of standardization in data schema, which impedes the integration of risk data across systems.
- As AI expands, few studies address how people make risk decisions using transparent, accountable, algorithmically biased governance and ethics.

3.8.5 Summary of Findings

Overall, the reviews suggest that AI and digital technologies are being increasingly incorporated into PRM, particularly in infrastructure and construction projects. Techniques such as Machine Learning (ML), Natural Language Processing (NLP), fuzzy logic, Building Information Modeling (BIM) and Digital Twin (DT) offer clear improvements in the prediction, identification and monitoring of risks.

However, adoption across industries and lifecycle phases remains uneven and meaningful barriers persist due to the lack of interoperability, governance and access among SMEs. These perceptions will inform analysis of the results in the next chapters, in which a conceptual framework is what is proposed for AI-improved PRM.

3.9 Chapter Summary

This chapter presents the methodology and results of a Systematic Literature Review (SLR) conducted in accordance with the PRISMA statement. Initially, 759 articles were retrieved using Scopus as the main database and the structured query. After the screening of the sources and full-text eligibility checks, 14 systematic literature reviews were included in the synthesis.

The methodology involves the following steps: definition of research questions, database search, inclusion/exclusion criteria, screening and selection sources, and the structured data extraction process. This review adheres to PRISMA guidelines, which strengthens the transparency, replicability and overall robustness of the findings.

The results reveals key descriptive and analytical trends:

- Recent research on AI in PRM has grown rapidly, with most reviews being published between 2022 and 2025.
- The strong concentration of research in the AEC sector, driven largely by BIM and DT applications, contrasts with the limited exploration of other industries.
- AI and data-driven techniques such as ML, NLP, big data analytics and fuzzy logic are concentrated on risk identification, analysis and monitoring. However, risk planning and closure phases are rarely addressed.
- Gaps include SMEs only adopting tools to a limited extent, systemic/global risks not receiving sufficient coverage and studies failing to examine cross-sectoral issues. Additionally, people pay insufficient attention to ethics and governance when adopting AI.

This chapter provides a consolidated evidence base by integrating perceptions from fourteen systematic literature reviews. The importance capability of AI to reshape PRM is demonstrated, although adoption remains uneven and is also constrained by governance, methodological and sectoral barriers. These findings provide a solid foundation for Chapter 4, in which all the evidence is analyzed and mapped into PMBOK and ISO 31000 processes.

Chapter 4

Results of the Systematic Literature Review

4.1 Overview of Selected Studies

The fourteen studies identified through the systematic literature review feature a variety of project contexts, methodological approaches and disciplinary perspectives. Together, they demonstrate the slow yet clear blending of Artificial Intelligence (AI) into Project Risk Management (PRM).

Many studies adopt a broad perspective, analyzing the adoption of AI across project management as a discipline. These studies, also, apply categories to AI and data-driven techniques, and highlight areas in which predictive modeling and monitoring are adopted, identifying barriers such as lack of expertise and organizational resistance. *(Adamantiadou & Tsironis 2025).*

Other SLRs focus on specific sectors, sharing all their detailed empirical evidence. For instance, researchers within the Architecture, Engineering and Construction (AEC) industry have explored how big data analytics, Machine Learning (ML) and Building Information Modeling (BIM) can be combined to anticipate risks such as cost overruns and schedule delays *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023).* Additional studies analyze the integration of Digital Twins (DTs) with BIM, emphasizing how real-time monitoring, predictive simulation and IoT-based dashboards support proactive risk management in digital construction *(Sepasgozar et al. 2023).* Moreover, BIM is also used for risk identification, safety monitoring and lifecycle management in context-specific reviews of transport infrastructure, including bridges, tunnels and roads, although interoperability challenges remain significant *(Costin et al. 2018).* Another contribution focuses on existing buildings, demonstrating how incomplete or uncertain data in retrofit and deconstruction projects necessitates improved modeling standards, AI integration and data-driven techniques *(Volk, Stengel & Schultmann 2014).*

Moreover, beyond the construction supply chains, studies have demonstrated that fuzzy logic along with AI-driven simulations can anticipate cascading disruptions and improve the management of supplier risk *(Baghalzadeh Shishehgarkhaneh et al. 2024)*. In SMEs, however, AI adoption remains limited, as a lack of resources and technical staff, as well as lower levels of digital maturity obstruct the systematic use of AI and data-driven methodologies in PRM. Nevertheless, lightweight, cloud-based AI solutions are view as a promising way for SMEs to access risk management capabilities that have traditionally been limited to larger organizations *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

AI is also applied in unconventional ways such as R&D and open innovation projects. Using text mining and NLP techniques, risk-related perceptions from patents, academic publications and project reports are extracted. This demonstrates how AI can support the risk identification in contexts where uncertainty is tied to knowledge flows rather than supply chains or costs *(Prasetyo et al. 2025)*.

Finally, some studies consider PRM via the systemic lens of governance. As global risk factors analysis shows, political, economic and social uncertainties directly affect construction cost performance, proposing fuzzy decision support methods to model such complexity *(Baloi & Price 2003)*. Moreover, a study on Public-Private Partnerships (PPPs) emphasizes the importance of appropriate risk allocation and transparent procurement processes, which are crucial for project success *(Osei-Kyei & Chan 2015)*.

Together, these fourteen publications reveal an uneven but steadily growing interest in the integration of AI and data-driven techniques within PRM. The dominant tools in construction and infrastructure projects include BIM, Digital Twin and predictive analytics, which have been adopted at a clear lead. However, SMEs, PPPs, innovation projects and global risk analysis show more limited but increasingly relevant developments. Collectively, the studies indicate that AI and data-driven methodologies are still at an early stage of maturity within PRM, yet their use is gradually expanding across different project types and contexts, paving the way for broader adoption alongside more standardized approaches.

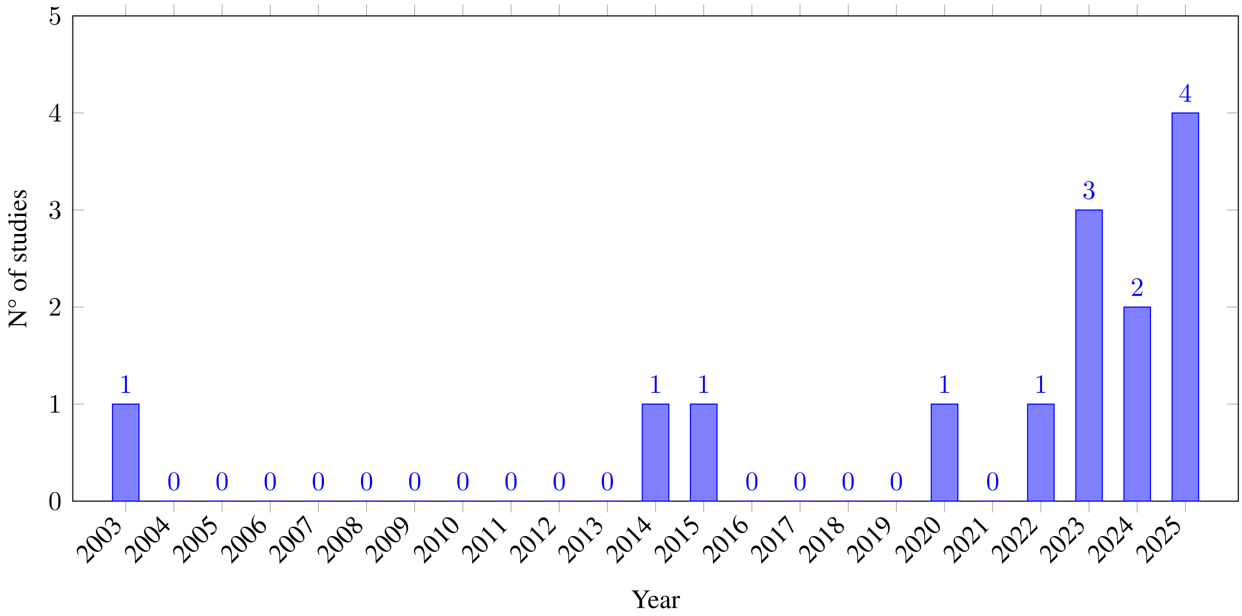

Figure 4.1: Distribution of studies published from 2003 to 2025

4.2 AI and Data-Driven Techniques in Project Risk Management

The systematic literature review highlights a variety of AI and data-driven techniques that support the different stages of PRM. These techniques are not isolated but rather form a family of complementary approaches that can be adapted to specific project contexts and risk processes.

4.2.1 Machine Learning (ML)

Machine Learning (ML) represents the most widely documented AI technique in the reviewed studies, particularly within the AEC and infrastructure domains. ML models are used to identify patterns in historical project data and to predict risks such as schedule delays, cost overruns, equipment failures and supply disruptions. Supervised learning algorithms support risk classification and probability estimation, while regression-based models provide early-warning indicators by uncovering correlations between project conditions and adverse outcome *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*.

The contribution of ML lies primarily in improving the accuracy and automation of quantitative risk assessment. By processing large datasets, ML supports data-driven decision-making and reduces the subjectivity that traditionally characterizes qualitative PRM methods. The examined studies emphasize that ML is particularly effective when integrated with structured digital environments and high-frequency datasets, as this enables continuous model refinement and adaptive predictions across the project lifecycle *(Salimimoghadam et al. 2025)*).

4.2.2 Natural Language Processing (NLP)

Natural Language Processing (NLP) allows PRM systems to extract risk-relevant information from large volumes of unstructured textual data, such as project reports, technical specifications, stakeholder communications and patent descriptions. NLP enables automated detection of risk indicators through keyword extraction, topic modeling and sentiment analysis, enhancing the coverage and consistency of risk identification processes *(Prasetyo et al. 2025)*.

The reviewed studies highlight that NLP is especially valuable in contexts where knowledge is dispersed across textual sources, including innovation projects, R&D portfolios and multi-stakeholder environments. NLP increases transparency by systematizing information that would otherwise require extensive manual review, thereby reducing oversight and improving the visibility of emerging risks.

4.2.3 Big Data Analytics and Internet of Things (IoT)

The examined publications highlight that NLP is especially valuable in contexts where knowledge is dispersed across textual sources, including innovation projects, R&D portfolios and multi-stakeholder environments. NLP increases transparency by systematizing information that would otherwise require extensive manual review, thereby reducing oversight and improving the visibility of emerging risks *(Sepasgozar et al. 2023)*.

Big Data platforms allow project teams to consolidate heterogeneous datasets, ranging from environmental conditions to equipment status, and to visualize risk indicators through dashboards and analytics tools. The reviewed SLRs show that IoT-enhanced monitoring strengthens PRM responsiveness by shifting practices from periodic reporting to real-time situational awareness. These technologies are particularly prominent in construction, infrastructure and asset-intensive projects, where physical operations generate rich data environments *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*

4.2.4 Fuzzy Logic and Expert Systems

Fuzzy Logic and expert systems support risk analysis and evaluation in contexts characterized by incomplete, uncertain or qualitative data. Instead of relying on precise numerical values, fuzzy systems model ambiguous conditions using linguistic variables. This makes them useful for evaluating cascading risks, supplier dependencies and complex inter-organizational networks *(Baghalzadeh Shishehgarkhaneh et al. 2024)*.

Expert systems formalize domain knowledge through rule-based structures, offering structured decision support when historical data are limited or not fully reliable. Studies emphasize that these techniques allow PRM teams to incorporate expert judgment in a transparent and repeatable manner, mitigating the subjective inconsistencies typically associated with qualitative assessments *(Baloi & Price 2003)*.

4.2.5 AI-Driven Simulation and Optimization

Simulation and optimization techniques enhance PRM by allowing project teams to test alternative scenarios and mitigation strategies before implementation. Simulation models, including Monte Carlo simulations, agent-based models or system dynamics, estimate the probabilistic impact of risks under different assumptions. These tools support scenario comparison and help quantify uncertainty in resource allocation, scheduling and cost management (*Baghalzadeh Shishehgarkhaneh et al. 2024*; *Rahi, Bourgault & Preece 2022*).

Optimization methods complement simulation by identifying the most effective risk response among multiple options. Techniques such as genetic algorithms, constraint-based solvers or reinforcement learning allow iterative search for optimal solutions, improving the consistency and quality of risk-response. (*Adamantiadou & Tsironis 2025*; *Salimimoghadam et al. 2025*).

4.2.6 Building Information Modeling (BIM) and Digital Twin (DT)

Building Information Modeling (BIM) and Digital Twins (DT) provide integrated digital environments that combine geometric, semantic and real-time data. BIM enables structured representation of assets and processes, supporting risk detection through clash analysis, construct-ability assessments and design consistency checks *(Costin et al. 2018)*.

Digital Twins extend BIM models by synchronizing them with sensor-based data during project execution. This integration supports continuous monitoring, simulation of real-world conditions and rapid evaluation of risk scenarios. The reviewed studies emphasize that BIM and DTs enhance PRM through improved visibility, collaborative risk assessment and lifecycle-oriented monitoring across planning, construction and operation phases. *(Sepasgozar et al. 2023; Volk, Stengel & Schultmann 2014)*.

		AI & DATA-DRIVEN TECHNIQUES					
		ML	**NLP**	**Big Data & IoT**	**Fuzzy Logic**	**Sim. & Opt.**	**BIM & DT**
STUDIES	Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023	x		x			
	Adamantiadou & Tsironis 2025	x				x	
	Salimimoghadam et al. 2025	x	x			x	
	Prasetyo et al. 2025		x				
	Sepasgozar et al. 2023			x			x
	Costin et al. 2018			x			x
	Baghalzadeh Shishehgarkhaneh et al. 2024				x		
	Baloi & Price 2003				x		
	Volk, Stengel & Schultmann 2014						x

Table 4.1: Mapping AI & data-driven techniques to studies

In summary, AI is not a single technology but rather a family of AI and data-driven approaches that, when combined, can greatly reinforce PRM. Their adoption is most advanced in construction and infrastructure projects, while other contexts (SMEs, innovation projects, global risk governance) are still in early stages. The challenge ahead is to move from fragmented applications to integrated cross-sectoral frameworks aligned to standards such as PMBOK and ISO 31000.

4.3 Mapping AI and Data-Driven Techniques to PRM Processes

Aligning the findings from the examined systematic literature reviews with PRM processes defined in PMBOK and ISO 31000 provides a clearer picture of how AI and data-driven techniques are currently applied and where gaps remain.

4.3.1 Risk Identification

Systematic scanning of structured and unstructured data sources improves identification through NLP, data mining and BIM models. For instance, in open innovation projects, NLP is used to detect technological or market risks early on in patents and publications *(Prasetyo et al. 2025)*. In construction, BIM models enriched with IoT data can highlight early signs of design clashes or equipment failures, which may lead to project risks *(Sepasgozar et al. 2023)*.

4.3.2 Risk Analysis

Machine Learning (ML) and predictive models can strengthen both quantitative and qualitative risk analysis. In the AEC sector, ML trained on historical project data can predict risks more accurately than traditional probability-impact matrices *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. Fuzzy logic and expert systems complement this by modeling uncertainty. This is evident in incomplete datasets, such as those found in multi-tier supply chains *(Baghalzadeh Shishehgarkhaneh et al. 2024)*.

4.3.3 Risk Evaluation

Systematic literature reviews confirm the value of fuzzy logic for evaluating interdependent and cascading risks, which is consistent with the ISO 31000 principle of explicitly considering the uncertainty. Fuzzy decision support methods are more effective than conventional evaluation tools *(Baloi & Price 2003)*. For example, global political and economic risks affect construction cost performance.

4.3.4 Risk Response

Project teams can test and implement alternative mitigation strategies using AI-enabled simulations in a variety of conditions. This makes evidence-based decision-making easier since it replaces intuition with a limited scenario analysis. Simulation and optimization models support proactive planning by identifying mitigation options. The most effective one can then be identified prior to implementation *(Adamantiadou & Tsironis 2025)*.

4.3.5 Risk Monitoring and Control

Dashboards use real-time big data analytics to operationalize the dynamism principle of ISO 31000. In the AEC sector, continuous monitoring results from IoT sensors within BIM and DT platforms.

This monitoring is useful for assessing structural health and operational conditions. This enables to detect anomalies much earlier, such as bridges at risk of collapse or construction projects exceeding their budget *(Costin et al. 2018*; *Sepasgozar et al. 2023)*.

4.3.6 Risk Communication and Consultation

NLP-based applications support structured consultation processes by analyzing stakeholder perceptions, meeting minutes or communications logs. This improves both inclusiveness and transparency in line with the principle of stakeholder engagement of ISO 31000 *(Prasetyo et al. 2025)*.

		PRM PHASES					
		Identification	**Analysis**	**Evaluation**	**Response**	**Monitoring**	**Communication**
AI & DATA-DRIVEN TECHNIQUES	**ML**	Predictive detection	Cost/delay modeling	Quantitative evaluation	Data-driven planning	Continuous learning	–
	NLP	Text mining	–	–	–	–	Stakeholder analysis
	Big Data & IoT	Real-time detection	Trend analysis	Evaluation dashboard	Scenario analysis	Monitoring dashboard	Transparency dashboard
	Fuzzy Logic	–	Risk classification	Systemic evaluation	Decision support	Monitoring networks	–
	Sim. & Opt.	–	–	Scenario evaluation	Mitigation testing	Scenario review	–
	BIM	Design clash detection	Integrated risk data	Lifecycle evaluation	Mitigation planning	Lifecycle monitoring	Visual dashboard
	DT	Early detection	Predictive modeling	Simulation evaluation	Response simulation	Continuous monitoring	Shared dashboard

Table 4.2: Mapping AI & data-driven techniques to PRM phases

Although risk planning in the initiation and closure phases remains largely untouched by AI and data-driven techniques, the mapping suggests future opportunities. For example, systematic literature reviews on PPPs emphasize the importance of allocating risk at project initiation, an area in which AI and data-driven methodologies could provide support in negotiating contracts and allocating models.

Similarly, systematically capturing and analyzing lessons learned at project closure is a promising but unexplored application for AI *(Osei-Kyei & Chan 2015)*.

Overall, the mapping shows that AI and data-driven techniques are operational across PRM processes, especially in identification, analysis and evaluation, as well as monitoring. However, initiation and closure require future integration.

4.4 Contexts of Applications

Evidence from the 14 identified publications confirms that AI and data-driven techniques are adopted unevenly across PRM contexts, with construction and infrastructure clearly leading the way. Domains such as SMEs, PPPs, innovation projects and global risk analysis appear less frequently. Nevertheless, they provide valuable insights into emerging opportunities and challenges.

4.4.1 AEC Industry

The AEC industry is by far the most analyzed context for the adoption of AI and data-driven techniques within PRM. Several studies emphasize that monitoring is being improved and risks are being predicted via the adoption of machine learning, BIM, digital twins and big data. ML models that are trained using historical project data can detect early warning signs of cost overruns or schedule delays more accurately than traditional methods *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. BIM and DTs are particularly significant as they integrate data from multiple project phases and sources, providing managers with comprehensive insight into project risks. DTs also simulate project conditions in real time, enabling stakeholders to test "what-if" scenarios and then selecting mitigation strategies before implementation *(Sepasgozar et al. 2023)*.

4.4.2 Transport Infrastructure

Within the AEC domain, one systematic literature review focuses on transport infrastructure projects. Here, BIM plays a central role in safety monitoring and lifecycle management of bridges, tunnels and roads *(Costin et al. 2018)*. The studies highlight both the opportunities, such as improved risk identification and safety enhancements, as well as the barriers, particularly the lack of interoperability in BIM standards. These challenges hinder the full integration of AI and data-driven methodologies into risk management processes, as technical constraints are a significant obstacle.

4.4.3 Existing Buildings

Another publication focuses on existing buildings, particularly in maintenance, retrofitting and deconstruction projects. The studies highlight that risks are frequently related to incomplete or uncertain data, such as missing information on structural conditions or lifecycle costs *(Volk, Stengel & Schultmann 2014)*. While BIM is identified as a tool that can reduce this uncertainty, its effectiveness largely depends on standardizing and improving data using AI-based analytics.

4.4.4 Small and Medium Enterprises (SMEs)

The adoption of AI and data-driven techniques in small and medium enterprises remains limited, reflecting the digital divide between larger firms and smaller organizations. The examined publication shows that SMEs face significant barriers such as scarce resources, limited technical staff and lower levels of digital maturity. *(Ferreira De Araújo Lima, Crema & Verbano 2020)*. However, lightweight, cloud-based AI solutions are considered promising enablers, as they provide small and medium enterprises with access to risk management capabilities that were previously only available to large corporations. This highlights a significant gap in SME-focused PRM research.

4.4.5 Public-Private Partnership (PPPs)

The study analyzing PPP projects shows that the success of such projects depends heavily on appropriate risk allocation and transparent governance frameworks *(Osei-Kyei & Chan 2015)*. While not explicitly AI-focused, this publication is relevant because it highlights the governance dimension of PRM, which needs to be aligned with AI-enabled tools and data-driven techniques. The latter can particularly support contract negotiations and decision-support systems that allocate risks to the party best placed to manage them.

4.4.6 Global Risk Factors

Finally, one systematic literature review models global systemic risks, showing how political, economic and social uncertainties directly impact construction cost performance. These macro-level risks can be incorporated into project risk frameworks *(Baloi & Price 2003)*. Fuzzy decision support systems (DSS) are proposed as a means of doing so. This extends PRM beyond the project level and connects it to the broader environment in which projects are embedded.

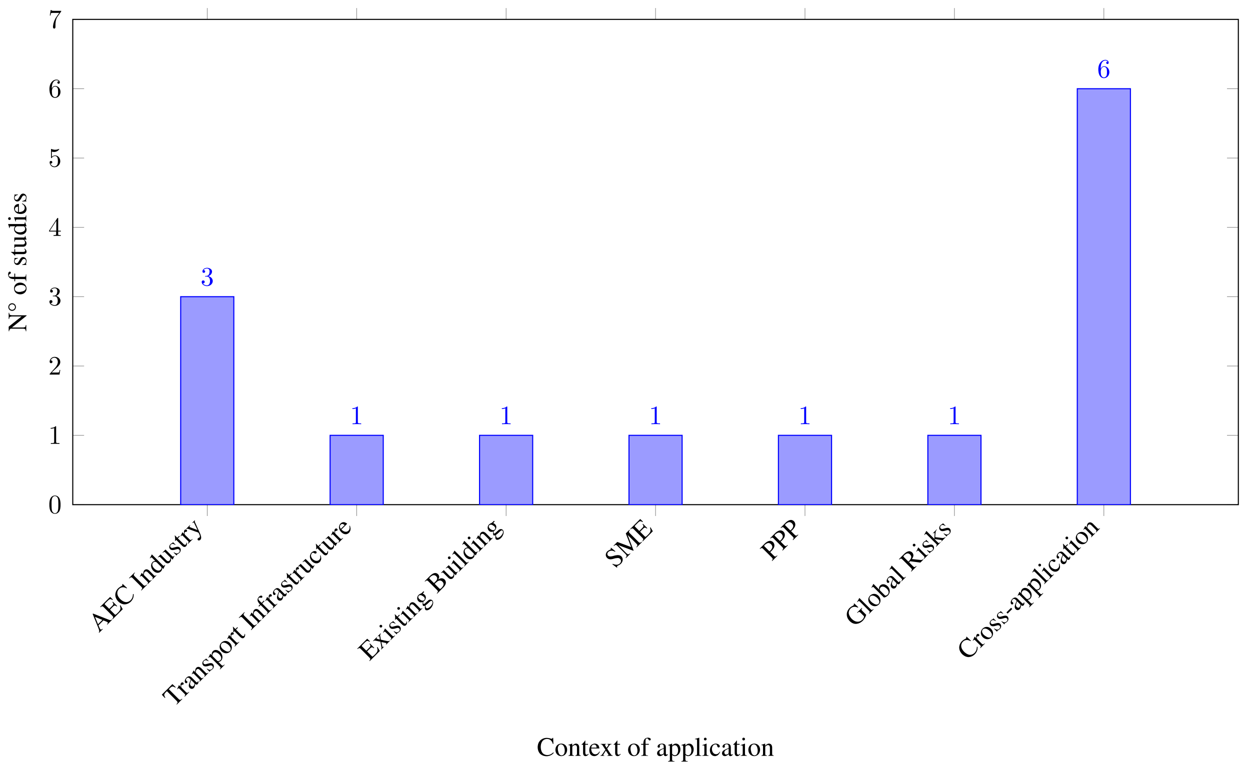

Figure 4.2: Number of studies per context of application

Collectively, the results suggest that while construction and infrastructure are leading the way in integrating AI and data-driven methodologies into PRM, other sectors highlight complementary challenges and opportunities, thereby broadening the perspective and indicating clear directions for future research and practice.

4.5 Enablers and Barriers to AI Adoption

The 14 systematic literature reviews analyzed reveal a consistent set of enablers and barriers that influence the adoption of AI and data-driven techniques in Project Risk Management (PRM). These factors cut across sectors and methodologies, highlighting both technical and organizational dimensions.

4.5.1 Enablers

Several elements are reported to be key factors for the success of AI and data-driven techniques within PRM:

- *Data availability and integration*[(1)]: machine learning and predictive analytics can now operate effectively thanks to the growing use of building information modeling, digital twins, IoT sensors and PMIS which create rich data environments *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023*; *Sepasgozar et al. 2023)*.

- *Digital transformation momentum*[(2)]: The construction sector is rapidly digitalizing and studies suggest that this momentum is accelerating with the adoption of AI and data-driven methodologies to identify and monitor risk. Technologies merging the Internet of Things (IoT), Virtual Reality (VR) and big data are critical enablers for predictive PRM *(Sepasgozar et al. 2023)*.
- *Leadership and organizational support*[(3)]: The examined studies highlight that successful adoption requires strong support from project leaders and executives, who must invest in cultural change, training and infrastructure *(Adamantiadou & Tsironis 2025)*.
- *Standardization and frameworks*[(4)]: The principles of PMBOK and ISO 31000 provide a recognized structure for PRM. AI integrates easily when innovations align with these established standards, which encourage systematic processes and transparency *(Salimimoghadam et al. 2025)*.
- *Cloud-based solutions*[(5)]: Lightweight cloud-based platforms reduce the entry barriers for SMEs by providing affordable access to AI-enabled and data-driven risk management tools *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.

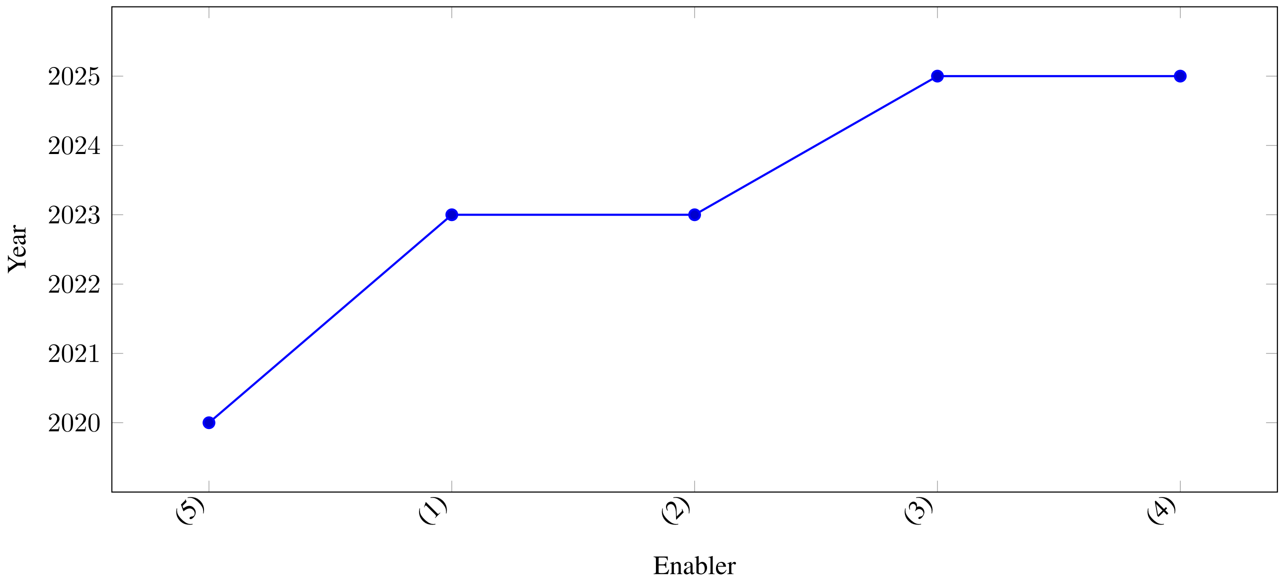

Figure 4.3: Enablers by year

		ENABLERS				
		Data availability and integration	**Digital transformation momentum**	**Leadership and organizational support**	**Standardization and frameworks**	**Cloud-based solutions**
STUDIES	Ferreira De Araújo Lima, Crema & Verbano (2020)					x
	Salimimoghadam et al. (2025)			x	x	
	Sepasgozar et al. (2023)	x	x			
	Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera (2023)	x				
	Adamantiadou & Tsironis (2025)		x	x		

Table 4.3: Mapping enablers to studies

4.5.2 Barriers

At the same time, several obstacles hinder the effective adoption of AI and digital methodologies within PRM:

- *Data quality and interoperability*(1): Multiple studies emphasize that while data is abundant, it is often fragmented, inconsistent or locked in isolated systems. For instance, studies on BIM and infrastructure project highlight interoperability issues, particularly the lack of unified standards (*Costin et al. 2018*; *Volk, Stengel & Schultmann 2014*).
- *High implementation cost*(2): AI and digital tools, especially for the ones requiring advanced infrastructure such as DT platforms, require significant financial investments, which many organizations, particularly SMEs, cannot afford *(Ferreira De Araújo Lima, Crema & Verbano 2020)*.
- *Skills and expertise gap*(3): A recurrent barrier across studies is the shortage of skilled professionals capable of implementing, interpreting and maintaining AI and data-driven systems. This dependency reinforces reliance on external experts consultants and obstructs adoption

(Salimimoghadam et al. 2025).

- *Cultural and organizational resistance*[(4)]: Resistance to change, especially in construction sectors that traditionally rely on established methods, hinders AI uptake. Studies emphasize that the adoption of AI and data-driven techniques is not just a technical matter, but also an organizational cultural one *(Adamantiadou & Tsironis 2025).*
- *Governance and ethical concerns*[(5)]: Few examined studies directly address governance and ethical concerns such as transparency, accountability and algorithmic bias, yet these greatly hinder the wider acceptance of AI-enabled PRM. In contexts such as PPPs, governance is particularly critical, as robust frameworks and AI-based, data-driven decision support systems can lose credibility *(Osei-Kyei & Chan 2015).*

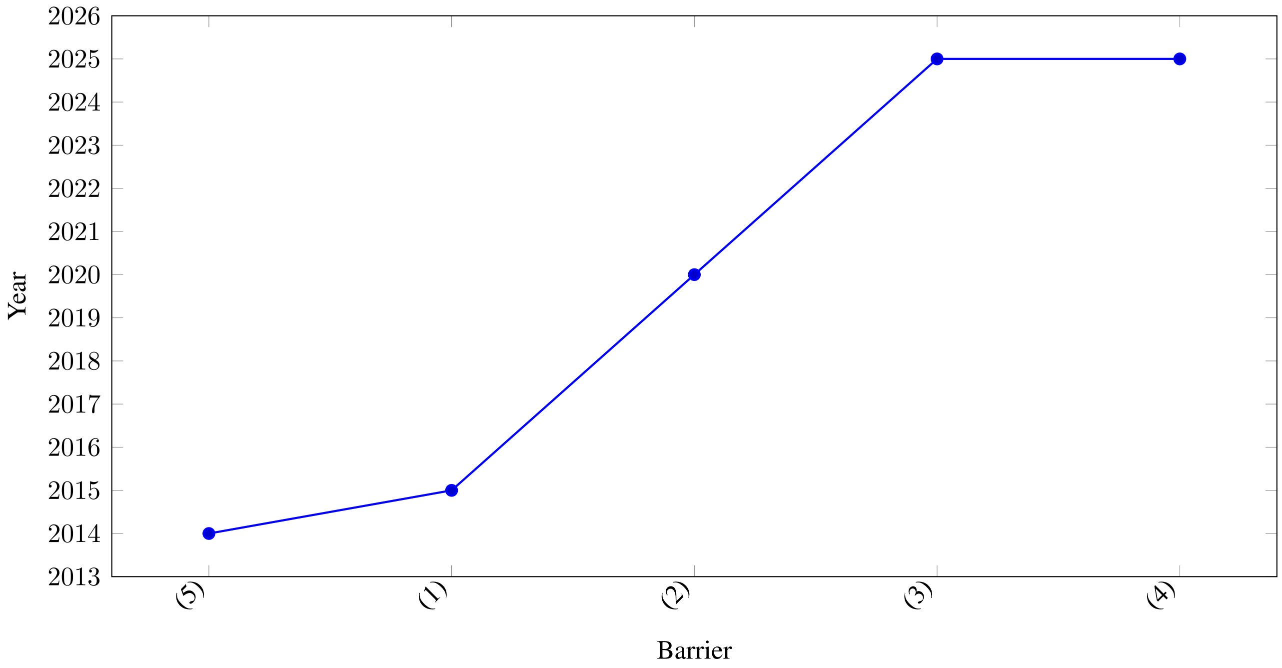

Figure 4.4: Barriers by year

		BARRIERS				
		Data quality and interoperability	**High implementation cost**	**Skills and expertise gap**	**Cultural and organizational resistance**	**Governance and ethical concerns**
STUDIES	Ferreira De Araújo Lima, Crema & Verbano (2020)		x			
	Salimimoghadam et al. (2025)			x		x
	Sepasgozar et al. (2023)		x			
	Volk, Stengel & Schultmann (2014)	x				
	Costin et al. (2018)	x				
	Adamantiadou & Tsironis (2025)			x	x	
	Osei-Kyei & Chan (2015)					x

Table 4.4: Mapping barriers to studies

In summary, the analyzed systematic literature reviews suggest that AI and digital methodologies enable PRM through technology, data integration, digitalization, leadership and standards. However, organizations and cultures can also create barriers through governance. A recurring theme across all the studies is the tension created by many technological possibilities and limited practical uptake. Capacity building and technical development are also necessary. Finally, to unlock the full potential of AI-improved PRM, additional governance innovation and cross-sectoral learning are needed.

4.6 Research Gaps

Although the body of literature on the adoption of AI and data-driven techniques within PRM has grown significantly in recent years, the studies indicate that the field is still in its early stages of maturity. While the 14 systematic literature reviews examined provide important insights, they also reveal significant limitations that must be addressed by future research.

A first recurring gap is the scope of the project lifecycle. AI and data-driven applications primarily focus on identifying, analyzing and monitoring risk. However, the initiation and closure phases remain largely neglected. For example, studies on PPPs emphasize the importance of early risk assignment, yet AI is rarely used to support this critical decision-making process *(Osei-Kyei & Chan 2015)*. Similarly, few contributions explore how lessons learned at project closure could be systematically captured and fed into predictive models for future projects *(Volk, Stengel & Schultmann 2014)*.

A second limitation is the sectoral distribution of applications. The evidence shows a strong emphasis on construction and infrastructure, where BIM, DTs and predictive analytics are widely adopted (*Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023*; *Sepasgozar et al. 2023*). While other areas, such as SMEs and innovation projects, are less represented.

Significant technical barriers also emerge. Data is often abundant, but fragmented, inconsistent and incomplete. These issues make it difficult to train AI and data-driven models in an effective way. Interoperability problems persist in BIM and infrastructure systematic literature reviews, especially regarding data standards and schema definitions, which prevent integration across platforms. (*Costin et al. 2018*; *Volk, Stengel & Schultmann 2014*). Another under-explored dimension is scalability: little is known about how these methods can be applied across portfolios or multi-project environments, even though most studies describe applications at the project level *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*.

SLRs at the organizational level highlight challenges relating to skills, costs and culture. Many firms lack professionals with training in project management and AI, forcing them to rely on external consultants. Adoption is constrained by the high cost of implementation, especially for SMEs. Cultural resistance is also evident as traditional practices remain deeply entrenched and widely integrated across sectors. Together, these factors limit the move towards common use of experimental applications (*Salimimoghadam et al. 2025*; *Adamantiadou & Tsironis 2025*).

Finally, there are important gaps in governance, ethics and transparency. Very few studies discuss how AI-enabled and data-driven tools can promote inclusiveness and accountability, both of which are emphasized by ISO 31000 and PMBOK. The current debate barely addresses issues such as algorithmic bias, decision accountability and ethical implications. Although the literature recognize the importance of governance for PPPs success, the support that AI and digital methodologies could provide for oversight and transparency remains theoretical *(Osei-Kyei & Chan 2015)*.

In conclusion, while AI and data-driven techniques are progressively shaping PRM practices, their potential remains only partially realized. It is important to bridge this gap by moving from broken applications to complete frameworks that align AI-enabled and data-driven PRM with the principles and processes of the PMBOK and ISO 31000.

4.7 Chapter Summary

This chapter presents the results of a systematic literature review conducted on 14 studies published between 2003 and 2025. The analysis shows that, while people are increasingly integrating AI-enabled and data-driven techniques into PRM, adoption across sectors is fragmented and uneven.

The findings confirm that these approaches can strengthen PRM by improving risk identification and predictive analysis, supporting evaluation under uncertainty and enabling continuous monitoring through data-rich environments. Techniques such as machine learning, natural language processing, big data analytics, fuzzy logic, simulation, as well as BIM and DT, reinforce traditional risk management practices in complementary ways.

At the same time, the studies highlight that progress is concentrated in construction and infrastructure, while other areas such as innovation projects, SMEs and public sector initiatives are less explored. Common enablers include digitalization momentum, data availability, leadership support and the role of international standards. In contrast, adoption is hindered by data quality and interoperability issues, high implementation costs, skills shortages, cultural resistance and a limited focus on governance and ethical principles.

Taken together, the results underline that AI and data-driven PRM are still in the early stages of development. The challenge ahead is to move from isolated applications toward integrated, cross-sectoral frameworks that are aligned with recognized standards such as PMBOK and ISO 31000, and that embed transparency, accountability and explainability into their design.

Chapter 5

Discussion and Conceptual Framework

5.1 Introduction

The purpose of this chapter is to provide an interpretive account of the examined studies, moving beyond the presentation of results in Chapter 4. Discussion chapters not only summarize the key findings of the analyzed systematic literature reviews but also interpret them and synthesize insights by considering theory, standards and practice. This is particularly important in the case of Project Risk Management (PRM) because the field of AI and data-driven applications is both recent and fragmented. The reviewed studies include contributions that explicitly address AI, such as those focused on mapping applications, challenges and opportunities, and others that emphasize broader digital approaches such as BIM, Digital Twins or simulation, along with their challenges and opportunities. Taken together, these studies reveal that technological transformation in PRM is already underway, but its application is highly uneven across processes and sectors.

The results presented in Chapter 4 demonstrate that these methodologies are currently influencing certain phases of the risk management cycle. Predictive models, natural language processing and dashboards with real-time data integration benefit risk identification, analysis, evaluation and monitoring. By contrast, initiation and closure phases are still under explored. Moreover, few contributions consider how AI could support early risk allocation or how digital tools could systematize the capture of lessons learned. A similar imbalance is evident in industries: construction and infrastructure mostly use advanced technologies thanks to BIM and DT platforms, but adoption remains limited among SMEs, public sector initiatives and governance contexts such as PPPs.

In this context, the chapter has two objectives. Firstly, to interpret all the findings in relation to recognized standards such as PMBOK and ISO 31000, assessing the extent to which AI and data-driven techniques reinforce the principles of transparency, systematic analysis and dynamism embedded in these frameworks. Secondly, to propose a conceptual framework for AI-enabled and data-driven PRM synthesizing techniques, processes, enablers and barriers into an integrated perspective. The final aim is to move from fragmented, sector-specific applications to more robust, cross-sectoral decision support systems that align with established standards and organizational needs.

5.2 Discussion of Main Findings

The analysis of the fourteen systematic literature reviews reveals both the opportunities and limitations of AI and data-driven techniques for Project Risk Management (PRM). A first area of discussion relates to the processes of PRM. Evidence suggests that Machine Learning (ML) and big data analytics can significantly enhance risk identification and analysis. For example, predictive models, when trained using historical project data, can anticipate cost overruns and schedule delays more accurately than probability-impact matrices and other traditional approaches *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. Similarly, supervised learning models within project databases provide early warning indicators so that managers can react before risks materialize *(Adamantiadou & Tsironis 2025)*.

Moreover, Natural Language Processing (NLP) expands on risk identification by enabling analysts to process unstructured information such as project reports, contracts and patents. NLP and text mining tools can detect risks within large bodies of text, highlighting issues that a human alone would miss *(Prasetyo et al. 2025)*.

Building Information Modeling (BIM) and Digital Twin (DT) applications, often combined with IoT sensors, are most closely associated with risk monitoring and review. Digital convergence platforms manage risk by transforming static documentation into dynamic, data-integrated environments *(Sepasgozar et al. 2023)*. BIM also enables lifecycle monitoring by reducing safety and maintenance risks in infrastructure projects, particularly in bridges, tunnels and roads *(Costin et al. 2018)*. Moreover, this technique helps to reduce uncertainty in retrofitting and deconstruction projects, although its effectiveness depends on data standardization and quality *(Volk, Stengel & Schultmann 2014)*.

Alternative modeling approaches also contribute to PRM digitalization. Fuzzy logic and expert systems can simulate cascading disruptions in construction supply chains and offer insights in situations in which traditional quantitative methods are inadequate *(Baghalzadeh Shishehgarkhaneh* *et al. 2024)*. Fuzzy models have also been applied to capture systemic political, economic and environmental risks, thereby extending the scope of PRM to macro-level uncertainties *(Baloi & Price 2003)*.

However, despite all these advances, meaningful gaps still exist. Firstly, the analyzed systematic literature reviews largely omit initiation and closure phases. Secondly, with the partial exception of the study on PPP projects, which consider just how governance allocates risk contractually, few discuss just how AI could support early decision-making or systematic learning upon project completion *(Osei-Kyei & Chan 2015)*. This omission reflects a broader trend in the project management literature. Risk, in fact, is often treated mainly as an operational concern rather than as a strategic element spanning the entire lifecycle.

A third theme concerns the contextual differences. Adoption is most advanced in the AEC sector, reflecting both strong pressures to manage cost and time overruns, and the availability of digital infrastructures such as BIM and DTs *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. By contrast, AI adoption in SMEs remains underdeveloped. Recurring obstacles include limited number of resources, skills shortages and lower digital maturity levels, although cloud-based AI platforms are considered a promising solution *(Ferreira De Araújo Lima, Crema & Verbano 2020)*. AI-enabled and data-driven solutions remain distant from public-private partnerships that emphasize governance and risk allocation. Meanwhile, studies of global risks demonstrate the potential of fuzzy modeling regarding systemic political and economic uncertainties *(Baloi & Price 2003)*.

Finally, enablers and barriers emerge as a fourth analytical dimension. According to several studies, adoption is driven by digitalization momentum, data availability and leadership support *(Salimimoghadam et al. 2025)*. At the same time, however, data fragmentation and lack of interoperability remain major barriers *(Volk, Stengel & Schultmann 2014)*. Other obstacles include high implementation costs, limited expertise and cultural resistance *(Adamantiadou & Tsironis 2025)*. A particularly critical gap concerns governance and ethics: very few studies address transparency, accountability or bias in AI-based and data-driven risk management decisions, with the main exceptions being broader AI systematic literature reviews and the one on PPP projects *(Osei-Kyei & Chan 2015)*.

In summary, AI and data-driven methodologies should be regarded as complement to traditional PRM rather than a substitute. While predictive capacity, objectivity and continuous monitoring are improved, current contributions remain uneven and fragmented across sectors and processes.

Without strong governance frameworks, their potential will only be partially realized. To avoid this, there must be sectoral diversification and integration across the full project lifecycle. The challenge, therefore is not whether these methods can support PRM, but how to integrate them systematically. Decision support systems aligned with standards such as PMBOK and ISO 31000 should facilitate this integration.

5.3 Developing a Conceptual Framework

The findings from the examined systematic literature reviews provide the foundation for developing a framework that demonstrates how AI-enabled and data-driven techniques can be integrated within the established processes of Project Risk Management (PRM) processes. The framework integrates three major dimensions:

1. the technological layer involving AI and data-driven tools;
2. the process layer aligning with standard PRM phases as defined in PMBOK and ISO 31000;
3. the contextual layer comprising organizational, cultural and governance enablers and barriers.

Through these dimensions, the framework articulates an interpretive model that captures the dynamic interaction between technology, process and context.

The technological layer encompasses a wide range of tools and techniques identified across the fourteen systematic literature reviews included in this study. Machine Learning (ML) contributes predictive capabilities by analyzing large datasets of historical project data and identifying correlations between risk factors and project outcomes *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*. Natural Language Processing (NLP) enables systems to automatically extract risk-related information from textual documents, contracts and patents *(Prasetyo et al. 2025)*. Big data analytics combined with Internet of Things (IoT) enables continuous data collection and real-time monitoring, improving situational awareness and early warning capabilities *(Sepasgozar et al. 2023)*. Meanwhile, Building Information Modeling (BIM) and Digital Twin (DT) integrate static and dynamic data throughout the project lifecycle, enabling organizations to visualize and simulate potential risk scenarios (*Costin et al. 2018*; *Volk, Stengel & Schultmann 2014*). Finally, fuzzy logic and AI-driven simulations provide valuable decision support when information is incomplete or uncertain *(Baghalzadeh Shishehgarkhaneh et al. 2024)*.

The process layer illustrates how these technologies are applied across the main stages of PRM, including risk identification, analysis, evaluation, response, monitoring and communication. As demonstrated in Chapter 4, applications mostly concentrate on identification, analysis and monitoring, while initiation and closure are seldom addressed. In the identification phase, NLP and text mining facilitate the early detection of potential risks from large volumes of unstructured data. During analysis and evaluation, ML and fuzzy systems can strengthen quantitative risk assessment and probabilistic modeling. For response, simulation and optimization tools test alternative mitigation strategies prior to implementation. Finally, BIM, DT and IoT improve review and monitoring, providing continuous tracking and active risk dashboards. However, the systematic literature review revealed that the communication phase is still underdeveloped. This phase involves aligning stakeholder and disseminating risk information, as well as using visual, data-driven tools to support transparency and collaboration.

The contextual layer captures the organizational and environmental conditions that determine the success of technology integration. Several enablers emerge consistently across all the reviewed studies. Data availability and digitalization momentum are among the most frequently cited, particularly in the AEC sector, where structured digital platforms are almost commonplace *(Sepasgozar et al. 2023)*. Leadership and organizational commitment also play a critical role, as the decision to invest in AI and related tools often depends on managerial awareness and strategic vision *(Salimimoghadam et al. 2025)*. In parallel, recognized standards and frameworks, such as PMBOK and ISO 31000, share vocabulary and structure, thereby aligning AI-based and data-driven tools with already established practices. However, significant barriers still hinder progress. Model reliability is weakened by data quality and interoperability issues, while high implementation costs and a lack of skills limit adoption, primarily among SMEs *(Ferreira De Araújo Lima, Crema & Verbano 2020)*. Cultural resistance continues to impede the transition from traditional to data-driven management practices. Most critically, governance and ethics receive limited attention, since such processes rarely embed transparency, accountability and bias mitigation in AI-supported risk processes *(Osei-Kyei & Chan 2015)*.

LAYER	FUNCTION
Technological	Analysis of available AI and data-driven techniques
Process	Integration of examined tools with PRM phases
Contextual	Definition of organizational enablers and barriers

Table 5.1: Framework dimensions

Bringing these dimensions together, the framework conceptualizes AI-enabled and data-driven PRM as a multi-layered decision support system. As its core, technological tools interact with PRM processes, feeding them with data, predictions and simulations. Around this core, organizational enablers and barriers act as moderating factors that either facilitate or hinder integration. Therefore, the framework reflects both the technical potential and the contextual complexity of digital PRM transformation.

In practical terms, the framework functions as an implementation roadmap, guiding organizations in the progressive integration of AI and data-driven methods in their existing risk management systems. The first step is to create a digital project data environment, in which information from BIM, IoT and PMIS is aggregated to ensure quality, interoperability and traceability. This establishes a foundational layer for the consistent use of both structured and unstructured data across the project lifecycle, providing the necessary infrastructure for future AI applications.

Secondly, once the data has been aggregated, AI-enabled tools can be embedded directly into PRM workflows. The initial focus should be on risk identification and monitoring, where data availability and feedback are richest. ML and NLP techniques can be used to detect problems in their infancy, while simulation and optimization models, such as Monte Carlo analysis, system dynamics, genetic algorithms and reinforcement learning, can be applied to evaluate mitigation strategies and optimize resource allocation before its implementation.

In the third stage, the organization sets up feedback loops to document, analyzes and learns from risk outcomes. This data is then used to improve predictive risk models that support risk assessment. In doing so, PRM is transformed from a maintenance activity into an iterative learning system, with lessons learned from each new project.

Ultimately, an AI-enabled, data-driven PRM architecture can be designed to optimize stakeholder trust and ensure regulatory compliance with PRM, in accordance with governance and standardization frameworks such as PMBOK and ISO 31000.

Taken together, these stages operationalize the conceptual framework and build a roadmap for data preparation, AI, adaptive learning and governance alignment that can be implemented in practice. In this way, the framework highlights the interlinkages and dependencies between technology, processes and context, and provides a roadmap with realistic targets for digital and smart PRM.

STEP	DESCRIPTION	FUNCTION
1	Data-driven tools integration	Consolidate BIM, DT, IoT and PMIS data for interoperability
2	AI-enabled tools integration	Embed ML, NLP, simulation and optimization techniques into PRM processes
3	Continuous learning	Capture outcomes, refine predictive models, build adaptive systems
4	Government alignment	Ensure transparency, accountability and compliance with PMBOK and ISO 31000

Table 5.2: Implementation roadmap

5.4 Implications

Building on the progressive framework introduced above, this section summarizes the implications that emerge from the integration of AI and data-driven techniques within PRM. The framework proposed in this chapter, therefore, provides a conceptual framework of how technology, processes and context interact in this regard, as well as practical guidance on how actors can incorporate AI-enabled, data-driven approaches into their projects. The chapter discusses how the path from data integration to governance alignment translates into appropriate research and practice outcomes in relation to three theoretical, managerial and policy issues.

5.4.1 Theoretical Implications

Theoretically, AI-enabled and data-driven systems have significant implications for PRM, primarily in terms of epistemology. This is because traditional frameworks have long relied on static, experience-based models and qualitative methods for managing uncertainty in both scenario building and sensitivity analysis. Other approaches, such as machine learning, simulation and optimization, introduces a predictive, data-driven logic capable of continuously learn from new data *(Zabala-Vargas, Jaimes-Quintanilla & Jimenez-Barrera 2023)*.

This transformation aligns PRM more closely with the principles of systematic analysis and continuous improvement found in PMBOK and ISO 31000 and replaces human expert-based decision-making with algorithmic systems. This necessitates hybrid theoretical models that integrate algorithmic capabilities with human cognition *(Salimimoghadam et al. 2025)*. Future studies could then focus on adaptive theoretical models that incorporate both technical learning and ethical responsibility into the core principles of risk management.

Furthermore, the framework highlights the need for PRM theory to become context sensitive. The level of digital maturity and data availability varies widely across application areas, from advanced adoption in construction and infrastructure to early experimentation in SMEs or PPPs. Theoretical models must also reflect that risk management capability is now indistinguishable from technological capability and organizational readiness.

5.4.2 Managerial Implications

The recommendations for managers are based on the roadmap described in the framework. Each phase, such as data integration, AI and data-driven tools deployment, learning and governance, provides actionable to guide organizations in the implementation of digital risk management processes.

Firstly, organizations should develop a digital data environment built on technologies such as BIM, PMIS and IoT platforms, since AI-enabled predictive models cannot function without reliable and interoperable data. Secondly, organizations can systematically incorporate AI tools into PRM processes to transform project delivery systems. AI techniques such as ML and NLP are well-suited to risk identification and analysis, while simulation and optimization techniques, such as Monte Carlo simulation, system dynamics or genetic algorithms, can enhance risk response and resource allocation well *(Adamantiadou & Tsironis 2025)*.

Thirdly, organizations should use continuous feedback mechanisms to learn dynamically from and update their predictive models as risk outcomes and business performance are tracked over time, thus making PRM a continuous learning process. Finally, successful implementation requires leadership commitment and alignment with governance frameworks. In fact, as studies demonstrate, leadership plays a very important role in providing vision, allocating resources and fostering a data-driven culture *(Salimimoghadam et al. 2025)*.

Taken together, these implications suggest an alternative managerial perspective. This considers AI not as an isolated tool but as a strategic enabler of resilience, transparency and continuous improvement. The roadmap provides a structure that allows gradual deployment, reducing technological and cultural resistance by integrating AI in an iterative way.

5.4.3 Policy and Governance Implications

From a policy perspective, the development of standards, interoperability protocols and ethical regulations is necessary to operationalize AI-enabled and data-driven PRM. The systematic literature review suggests that common data formats and integration mechanisms have yet to be established, particularly in BIM- and IoT-based research areas *(Costin et al. 2018)*. To ease cross-sector interoperability, policymakers and professional associations, such as PMI and ISO, should enable the development of open data standards and ontologies.

As algorithms are taking on greater responsibilities in project decision-making, authority over projects and questions around accountability arise if project decisions are made by algorithms. However, few studies have been conducted on algorithmic transparency and bias mitigation *(Osei-Kyei & Chan 2015)*. Regulatory frameworks are, therefore, necessary to ensure that the deployment of AI systems and risk-related decisions are subject to ethical standards.

Finally, education and credentialing frameworks should incorporate data analytics, AI governance and digital risk management to help PRM professionals prepare proactively for the hybrid, data-centric worlds increasingly adopted by the banking sector and many others.

5.4.4 Summary

In summary, the implications of AI-enabled, data-driven PRM extend across theory, management and policy. Theoretically, these approaches transform the generation and use of risk knowledge. From a managerial standpoint, they provide a roadmap for structured adoption within organizations. From a policy perspective, they focus on interoperability requirements, ethical guidance and training. Together, these factors have transformed PRM from a reactive function into a fundamentally calculated, dynamic and transparent one, as set out in both PMBOK and ISO 31000.

5.5 Conclusion

This chapter has discussed how AI and data-driven methods can contribute to PRM, suggesting a framework that integrates technology with processes and contexts. Based on the findings of the examined publications, the chapter demonstrates that the digitalization of PRM should be viewed as both a technical and organizational transformation. This can be used to derive a hierarchical implementation roadmap that incorporates the technology layer (AI and data-driven technologies), the process layer (PRM phases, from risk identification to perfomance monitoring) and the contextual layer (organizational facilitators and impediments).

The discussion confirms that these technologies are improving the predictive and analytical processes of PRM through methods such as machine learning, natural language processing, building information modeling and digital twin. Nevertheless, data integration, visualization and governance provide a roadmap for aligning the digital transformation with existing risk management standards and protocols.

Institutional maturity and governance are also important in addressing the challenges posed to PRM by AI. Aligning innovation with transparency and accountability is essential to maintaining trust in data-driven decisions. Therefore, as the framework suggests, the aim of PRM should be to build systems that learn responsibly from data while aligning with ethical and legal norms.

In summary, the chapter positions the proposed framework as both a theoretical and a practical contribution to the field. Researchers can use it to study digital transformation efforts in PRM, while practitioners can apply it to facilitate change. The remaining challenge is to operationalize the framework, evolving from experimentation to integrated, standardized and ethically governed AI-enabled PRM systems that reflect the roadmap developed in this study.

Chapter 6

Conclusions and Future Research Directions

6.1 Overview of the Study

This study investigates how PRM is evolving, in both conceptual and operational terms, alongside the emergence of AI and data-driven technologies. A systematic literature review has been conducted based on fourteen studies published between 2003 and 2025 to explore how digital and smart systems can be used to identify, analyze and mitigate project risks.

The findings highlight the increasing academic and professional interest in the intersection of digitalization and risk management. While early studies focused on the digitalization of traditional frameworks and their application to specific contexts, more recent works have begun to examine AI-enabled and anticipatory decision support systems for PRM. In developing a multi-layered framework of AI- and data-driven PRM, this study has centered on technological tools, risk management processes and contextual factors such as leadership, data governance and organizational culture.

By connecting these dimensions, the thesis demonstrates how AI and data-driven methods enhance the effectiveness of PRM while considering relevant professional standards, such as PMBOK and ISO 31000.

6.2 Summary of Key Findings

The systematic literature review and the resulting framework reveal a discipline undergoing profound change. More static, qualitative approaches are being supplemented by data-driven models that can learn and make probabilistic predictions.

Three key findings emerge from the research:

1. AI and data-driven techniques enhance PRM capabilities.
   The usage of machine learning, natural language processing, big data analytics, building information modeling, digital twins, AI-driven simulation and optimization tools enables predictive, real-time and adaptive risk management. This makes PRM less descriptive and more supportive of decision-making by providing timely and actionable information.
2. Integration remains uneven across PRM phases and across industries.
   Most applications focus on identifying, analyzing and monitoring risk, with few targeting risk initiation and closure. The AEC industry is the most advanced due to greater maturity of BIM and IoT infrastructure, whereas contexts such as SMEs and PPP projects are less experienced and at an earlier stage of development.
3. Organizational and governance factors are decisive for success.
   Promoting data availability, digital readiness and leadership commitment eases the adoption of digital solutions. Barriers include interoperability issues, high implementation costs, skills shortages and ethical concerns.

These findings provided the basis for the theory behind the proposed framework, which conceptualizes PRM as a multi-layered decision support system comprising core and outer levels. The core level comprises the technology that generates data, perceptions and simulations for PRM processes, while the outer level encompasses the broader organizational enablers and barriers. This model supports an adaptive learning system that can predict and manage risk using data.

6.3 Theoretical and Practical Contributions

This research provides several contributions to academic theory and managerial practice.

Theoretically, the study redefines PRM as a data-driven process and emphasizes that risk management is therefore determined by the organization's capacity to collect, analyze and interpret data. It also introduces the concept of hybrid governance, in which algorithmic and human decision-making coexist and complement each other. This approach is in line with recent studies on the adoption of transparency and explainability in AI-based project decisions.

From a managerial perspective, the thesis provides a roadmap that explain how to implement the identified digital opportunities. The roadmap highlights four sequential stages: data integration, AI tools adoption, constant feedback and governance alignment. It provides a structured guide for organizations looking to digitalize PRM and helps managers identify where to start, with reliable digital infrastructures, and how to transition toward smarter, standardized and ethically governed systems.

Finally, the thesis contributes to policy and professional development by highlighting the need for harmonized standards and education. Existing frameworks, such as the PMBOK and ISO 31000, provide a solid foundation; however, they need to evolve to incorporate competencies in AI, data analytics and digital governance.

6.4 Limitations of the Study

While the study provides a thorough synthesis of the literature, several limitations should be noted.

Firstly, this analysis is limited to secondary data drawn from published systematic literature reviews. This reflects the limitations of the underlying evidence base and may therefore be unable to capture potential emergent views or unpublished studies in these rapidly changing technological settings. Ideally, future research should include empirical analyses of primary sources.

Secondly, while the proposed framework provides an explicit and logical explanation of how AI and data-driven approaches can be leveraged within the PRM framework, the applicability of this framework to organizational risk identification, analysis and governance should be explored further in future research.

Thirdly, the literature is biased toward certain industries, such as the AEC sector. The findings may not be generalizable to other domains, such as finance, healthcare or the public sector, where digital maturity and the challenges of risk governance can vary widely.

6.5 Future Research Directions

Based on the findings from the examined publications and the multi-layered framework developed in Chapter 5, future research should aim to extend and validate the integration of AI and data-driven techniques in PRM. The three dimensions of the multi-layered framework (technological, processual and contextual) can systematically address the research gaps identified during the systematic literature review.

Regarding the technological dimension, it calls for a deeper empirical validation of AI and digital tools such as Machine Learning (ML), Natural Language Processing (NLP), Building Information Modeling (BIM) and Digital Twin (DT) *(Costin et al. 2018)*. Chapter 4 revealed that most papers discussing these technologies remain conceptual and demonstrate limited empirical testing in real project environments. Thus, future studies should examine these tools' predictive accuracy and field performance, providing evidence of their ability to support proactive risk recognition and management. Furthermore, technological fragmentation remains an issue, as interoperability across BIM, DT, IoT and PMIS platforms remains limited. Open data standards and common data integration protocols should be implemented to improve system interoperability, including automated data governance models to ensure the quality, traceability and transparency of project data. Researchers should also develop affordable and scalable AI tools tailored to SMEs because this is one of the most persistent barriers in the literature, affecting both technology and the economy.

From a process perspective, future research should expand the application of AI across all phases of the project lifecycle. As discussed in Chapter 4, most of the literature focuses on risk identification, analysis and monitoring, while the initiation and closure phases are rarely considered. However, AI and data-driven techniques could play a significant role in other phases, such as feasibility, risk allocation and predictive modeling, as well as in post-project evaluation and learning. Further work is needed to understand how to perform scenario-based simulations and optimizations to support decision-making, as well as to develop analytical capabilities for risk response. Additionally, a continuous data collection and feedback loop system must be developed to allow PRM to function as a learning system where models are continuously adjusted as planned in the framework into a self-improving risk management process.

The contextual dimension remains critical for successful implementation. As discussed in Chapters 4 and 5, organizational and governance constraints, such as skills shortages, cultural resistance and a lack of leadership commitment, still represent the major barriers to AI implementation. Future research should consider organizational and behavioral factors that enable or obstruct the use of AI in PRM. Important areas include leadership style, digital readiness and capability-building strategies for overcoming challenges associated with AI use. Future research could support the development of ethical and governance frameworks that integrate transparency, accountability and explainability with AI-supported decisions. Research could also verify whether the proposed framework can be generalized to other sectors, such as healthcare, information technology, finance and public administration, beyond the scope of the AEC industry. Additionally, future research should explore how project managers interact with AI, how they trust AI outcomes and how they justify decisions in hybrid human-AI settings, as these factors will influence the development of the next generation of data-driven PRM practices. Finally, AI-driven PRM should evolve to address systemic and global risks, including economic, political and environmental uncertainties that are not adequately modeled in current research.

RESEARCH GAP	FUTURE DIRECTIONS	FRAMEWORK LAYER
Lifecycle imbalance	Extend AI and data-driven techniques to initiation and closure phases	Process
Sectoral bias	Apply and test the framework in various sectors	Contextual
Technical barriers	Develop shared data standards for BIM, DT, IoT and PMIS	Technological
Organizational constraints	Design scalable, SME-accessible AI and data-driven solutions and promote adoption	Contextual
Lack of governance, ethics and transparency	Embed explainability and accountability in AI-based PRM	Contextual

Table 6.1: Mapping research gaps and future directions to framework layers

Taken together, these directions outline a coherent research agenda that bridges the gaps identified in Chapter 4 and the conceptual foundations established in Chapter 5. They also call for a shift that moves from theoretical models to empirical validation, from sector-specific analysis to cross-industry integration, and from technological readiness to ethical and institutional maturity. Taking these steps will be necessary if PRM is to become a smart, transparent and standardized digital discipline capable of managing uncertainty and enabling resilience within increasingly complex project ecosystems.

6.6 Final Remarks

In conclusion, this thesis demonstrates how AI and data-driven technologies are transforming PRM from a reactive control system into a predictive, transparent one. By analyzing fourteen systematic literature reviews, the study identified key gaps, such as limited lifecycle coverage, poor interoperability and weak governance, and synthesized them into a structured framework integrating technology, processes and context.

The proposed model, therefore, contributes both theoretically and practically by providing a systematic approach to implement AI-enabled and data-driven PRM aligned with established standards such as the PMBOK and ISO 31000. It also emphasizes the importance of leadership, ethical governance and data-driven culture to ensure the responsible integration of these technologies into PRM practices.

Ultimately, this work contributes to transforming PRM into a smart, standardized and ethically governed discipline that learns, adapts and handles uncertainty in an increasingly complex project environment.

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