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AI and Machine-Learning Readiness of Project Management Information Systems in Finnish Construction: A Literature Review and Interview Study

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ABSTRACT:

This thesis focuses on AI and machine-learning preparedness of project management information systems in Finnish construction. The gap in the existing research and practice is addressed in the study: although the use of PMIS is widespread, and the number of applications related to AI is increasing, the level of preparedness of existing PMIS environments to support AI and machine learning in real construction projects remains little known. The research is based on a systematic literature review, as well as a qualitative interview study of nine construction professionals in Finland. The literature review helped identify key dimensions of readiness, and the interview data were analysed thematically using NVivo. The findings suggest that PMIS preparedness for AI/ML in construction in Finland is neither complete nor absent, but partial and uneven. A partial foundation already exists in the form of digital tools, formal documentation practices, reporting environments and early uses of AI assistance. Nevertheless, preparedness is hampered by disjointed system landscapes, incomplete information streams, coexisting formal and informal communication habits, uneven trust in project information, unresolved governance challenges, and inconsistent organizational routines, support, and workflow fit. The current AI applications in project work are primarily restricted to narrow assistive activities like summarization, drafting, search and other support functions that are under human control. The thesis finds that PMIS in Finnish construction are moving toward AI/ML readiness, although they are currently better suited to assistive use than to a more integrated, AI-enabled PMIS capability. The next level of development will be based on the advancement of system integration, data quality and standardization, governance, trust, and alignment of digital tools with the practical project workflow.

KEYWORDS: Project management information systems, AI readiness, machine learning, Finnish construction, digitalisation, construction project management

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1 Introduction

1.1 Background

Construction projects involve a lot of different stakeholders clients, designers, con-tractors, subcontractors, suppliers, and public authorities and generate vast quanti-ties of diverse information materials (e.g. schedules, budgets, drawings, designs, Build-ing Information Models, Requests for Information, change orders, risk registers, con-tracts, safety reports) that need to be coordinated and integrated across different organ-izations and systems. Managing this information efficiently is important because inef-ficiencies in information management tend to result in higher costs, longer schedules, and lower-quality and less-safe outcomes. Reviews indicate that construction compa-nies suffer from significant schedule and cost overruns, and labor shortages. Still, ac-cording to Datta et al. (2024), construction lags behind in terms of digitalization in each and every project phase, which requires the development of digital competencies at the project level.

Project Management Information Systems (PMIS) are popular information systems in project-based organisations. In the construction industry, PMIS are used for planning and controlling the project scope, schedule and budget, managing documents and models, tracking risks and issues and facilitating communication and coordination between project team members. In practice, the "PMIS" of a construction project is usually a collection of separate (usually) interoperable software applications and tools like the primary project platform, scheduling, cost control, ERP, BIM, document management, email, and spreadsheets.

The main goal of PMIS is to provide a complete view of the status of a particular project so that timely and well-informed decisions can be made. However, some of the advantages of using such systems cannot be achieved due to the lack of cohesion among the applications and tools being used, the duplication of effort resulting from entering redundant data, and the inability of applications and data sources to function together effectively. As a result, PMIS can be viewed as the central repository of digital information regarding project management and decision making in construction, and their ability to support the use of data in more advanced ways will be a key factor in determining project success and organization-wide competitiveness.

Besides the strengths and weaknesses of PMIS, the literature on the two has been diversified by current PMIS studies. Systematic review of PMIS by Rebuglio et al. (2025) saw these as solutions to managing the vari-ety of aspects of a project, and showed that PMIS can be employed in managing pro-jects, programs, and portfolios by offering a single interface to the planning, sched-uling, monitoring, controlling, collaborating and risk management of all types of pro-jects. To sum up, Rebuglio et al. (2025) concluded that PMIS implementation on construction projects will help to ensure that construction projects do not exceed predetermined timeframes and budgets, and that the further development of PMIS use will also contribute to the better efficiency and further digitalization of the construction industry by making project planning, scheduling, collaboration, and task allocation more systematic.

Engineering projects are becoming increasingly complex due to their growing size and increasing reliance on technology, according to van Besouw and Bond-Barnard (2021); therefore, engineering projects require the development and implementation of sophisticated project management information systems (PMIS) in order to improve project efficiency and quality. In response to this necessity, van Besouw and Bond-Barnard (2021) developed the Smart Project Management Information Systems (SPMIS) concept to illustrate the architectures of such systems; the SPMIS architecture combines and analyzes data from multiple sources in order to support project intelligence. Van Besouw and Bond-Barnard (2021) argue that project data is often dispersed across multiple systems.

Similarly, there are concerns about data isolation and fragmented data in the area of construction AI research, where large volumes of engineering data exist in conjunction with limited adoption of AI techniques (Pan & Zhang, 2021; Ding et al., 2022). These findings indicate that the efficiency and performance of projects utilizing PMIS depends not only on the availability of data and tools, but also on integration, data quality, and organizational capabilities, which are the very foundation upon which the capacity of PMIS to support AI and machine learning will be built.

Meanwhile, AI and machine learning are being mentioned as the potential means of dealing with the ongoing issues in the management of construction projects. Abioye et al. (2021) state that the sector is characterized by the lack of productivity and a plethora of other issues that can be resolved with the help of AI, whereas Datta et al. (2024) attribute the endemic issues of construction project management, i.e., schedule and cost issues, to insufficient digitalization. In the whole field of project man-management, Müller et al. (2024) claim that the incorporation of AI into the project man-management is a groundbreaking phenomenon changing the industry, and Shang et al. (2023) say that the advent of AI and its different levels of implementation are prompting organizations to reconsider their strategic and functional capabilities to fulfill changing needs and stay afloat. Also, in construction management, in particular, Lai et al. (2025) mention that the construction industry is currently experiencing a transition to digital transformation at an unparalleled pace due to the fast development of AI and Industry 4.0, and Yang et al. (2025) state that AI applications are being introduced into several industries at an unprecedented rate, such as site monitoring and project management. A combination of these developments will characterize AI and machine learning as a larger shift in the paradigm of information collection, data analysis and use to make decisions about a project.

In this paradigmatic change, PMIS are now more and more likely to carry out more roles other than merely keeping and reporting project information. On the one hand, research and initial applications indicate that AI and ML models to anticipate delays, determine the risk of cost overruns, safety monitoring, quality management and automatic processing of textual and visual project data can be added to PMIS work process-es. In another meaning of the term, recent research in the field of generative AI in project management demonstrates that the project man-management field is being modified by generative AI technologies, such as chatbots (Felicetti et al., 2024), and project managers are beginning to adopt them to augment the already existing information systems. However, Fridgeirsson et al. (2023) also add that, due to the complexity, rapid develop-ment, and multi-dimensional nature of AI technology and management processes, no agreement on the AI effect on management has been reached yet, which implies that the practical manner in which PMIS can be of use to users and organizations has not been studied extensively. This poses highly tangible questions regarding the ability of the existing PMIS architectures, data, integrations, organizational capabilities, and governance structures to sup-port such functionalities when conducting regular operations in the construction in-dustry, where AI applications have quickly emerged, particularly regarding site monitoring and project management (Yang et al., 2025).

These global trends in digitalization and AI adoption are translated into a specific need in Finland to investigate how PMIS are currently employed and developed, and how capable they are of integrating AI and machine learning capabilities. The international literature provides evidence of both high hopes that AI can help solve long-standing problems in the construction sector (Abioye et al., 2021; Datta et al., 2024), as well as great uncertainty about how AI will ultimately change the way management systems and practices operate (Fridgeirsson et al., 2023; Müller et al., 2024). Therefore, this thesis has a clear justification for conducting this research: to evaluate the readiness of AI and machine learning of project management information systems that are currently in operation in construction projects, and to understand how project managers and planners perceive their current PMIS, future requirements and organizational conditions for implementing AI/ML-based functionalities. The subsequent sections will therefore narrow the general background into a specific research problem and gap, and then introduce the research objective, questions, and goals that will guide the systematic literature review and empirical interview study.

1.2 Research problem and research gap

Section 1.1 illustrated that the construction industry is very information intensive, that PMIS form the fragmented digital backbone of that information, and that there are growing expectations for AI and machine learning to support the delivery of projects while the reality of integrating those technologies into practice is still unclear. The combination of widespread use of PMIS systems, BIM, and digital tools, raises a concrete question for Finnish construction companies: how well are they positioned to support AI and machine learning through their current PMIS systems in both their technical and data bases as well as in terms of how the users and developers currently use and develop the systems? In this section, the discussions will be limited to the specific research problem and gap by examining the limitations of current PMIS used in construction, the fragmented efforts to use AI and ML in project and construction management, and the missing link between these two areas with respect to the AI and ML readiness of PMIS systems.

1.2.1 Limitations of current PMIS in construction

The literature has shown how PMIS have an important place in project-based organizations, however the same literature has illustrated the limitations of such systems. Rebuglio et al. (2025) show that PMIS support a wide range of project management functions. In construction, PMIS can contain one or more of the following; a platform for project collaboration, a document management system, project scheduling tools, a viewer for building information modeling (BIM), and/or a cost control or enterprise resource planning (ERP) system. These types of tools often come together as a patchwork system instead of a complete integrated system. Rebuglio et al. (2025) indicate there is significant fragmentation within the area and no common terminology and little if any dedicated outlet for publishing PMIS research that mirrors the fragmented nature of PMIS found in practice.

The fragmentation at the project level is evident in duplicate data entry from project team members, poor interoperability between PMIS, BIM and ERP systems, and the ongoing dependence by project teams on e-mail and spreadsheets to circumvent formal project platforms because either the information structure or workflow does not meet the needs of the project. Van Besouw and Bond-Barnard (2021) indicate that engineering projects are becoming increasingly complex and technology-intensive, Van Besouw and Bond-Barnard (2021) argue that increasingly complex engineering projects require more advanced PMIS, while also noting that project data is often scattered across different systems. Therefore, critical project information - time, cost, quality, risk, and resources -

is fragmented among multiple applications and formats. As a result, PMIS cannot provide an accurate, up-to-date picture of the overall project status.

In addition, the literature suggests that while PMIS are widely utilized, they are primarily being used for documentation, reporting, and regulatory compliance versus providing predictive or prescriptive decision-making support. Rebuglio et al. (2025) note that the PMIS literature still lacks clear functional definitions and sufficiently validated and generalisable models, indicating that the PMIS role in supporting more advanced analytics is not yet well defined. In practice, this can lead to systems that are very rich in recorded data but have limited built-in analytical capabilities. Project teams must then take the project data out of the PMIS and load it into a spreadsheet or other standalone application when deeper analysis is needed.

The above limitations are relevant to developing the readiness for AI and machine learning. To develop successful AI and ML models, a large volume of reliable, structured, and standardized data are necessary along with consistent and stable digital workflows in which predictions or recommendations can be incorporated into normal day-to-day work. Datta et al. (2024) emphasize that the implementation of AI and ML in actual projects remains constrained by data availability, data quality, and insufficient standardisation of digital workflows. Furthermore, the fragmentation of PMIS, poor integration with BIM and ERP systems, and the continuing reliance on informal tools, all exacerbate these issues. Thus, for this thesis, which is seeking to understand the current state of PMIS research and Finnish construction practice (RQ1) and to determine the factors that describe the readiness of AI/ML (Objectives 1-2), this represents the first component of the problem: existing PMIS configurations may not currently provide the integrated, high-quality data and stable processes that AI and ML would require; however, systematic evidence of this issue is rare.

1.2.2 Fragmented AI/ML efforts in project and construction management

Alongside the studies carried out on the development of PMIS, the popularity of Artificial Intelligence (AI) and Machine Learning (ML) in the project and construction management is steadily increasing. Nonetheless, according to Regona et al. (2022), despite numerous studies being performed worldwide regarding AI, not many studies have been com-pleted in the sphere of Project Management and even fewer in the Construction Sector. Bento et al. (2022) also suggest that the data on AI in project management are fairly scarce and unrelated, as the main subjects of the studies are the individ-ual tasks of the project management schedule, risk measure, and cost prediction. Thus, although there is substantial literature on the implementation of AI in the areas that project management interacts with, much of it is located in various and separate functional areas and does not present a comprehensive picture of AI-enabled project information man-management.

This opinion is also supported by the reviews on AI and ML in the construction. According to Datta et al. (2024), most AI and ML applications in the construction projects are focused on an individual task (cost estimation, scheduling, etc.), and very little is done on integrated lifecycle decision making. Regona et al. (2023) also state that despite the growing popularity of AI in the context of aiding decision-making in the construction industry, the combination of AI and digital platforms and project information systems is hardly ever mentioned in detail.

This suggests that the use of AI tools as a supplement that researchers and implementers of AI/ML typically use as an extra resource or external application processing a specific set of datasets is the norm, rather than as part of PMIS and routine project work. The fragmentation of the literature has two impacts on the present thesis . To begin with, the fragmentation restricts the existing understanding of how AI and ML can be practically incorporated into the intricate socio-technical landscape produced by PMIS, BIM, ERP and site systems on the construction projects. Secondly, since the literature provides a limited view of AI and ML's relationship to project management information systems and their current state and development, particularly in Finland, it also limits its utility in providing a com-plete response to RQ1.

1.2.3 The missing link: readiness of PMIS for AI and machine learning

The two themes of constraint of present PMIS and the disjointed AI/ML activities point to a lack of bridge; that is the willingness of the current PMIS in the construction industry to embrace AI and machine learning. In this thesis, PMIS readiness is understood as a socio-technical condition. Therefore it encompasses the technical aspects of the system architecture, interoperability and integration; the data-related aspects of availability, quality, structure and standardization; organizational aspects of skills, roles, resources and change capacities; human aspects of user attitudes, trust and perceived utility; and governance aspects of responsibilities, rules and alignment with organizational strategy. Datta et al. (2024) also specifically point out that future research needs to go beyond the technical development of AI and ML in construction to consider the or-ganizational, contractual and governance concerns that can influence the successful implementation of AI and ML in construction projects. This argument can be interpreted as a call for a more holistic conceptualisation of readiness, where AI/ML capacities can be found in current systems and organizational structures.

The previous studies of PMIS reveal fragmented landscapes of systems, the absence of consistent terminology, and ineffective project data environment (Rebuglio et al., 2025; van Besouw and Bond-Barnard, 2021). Simultaneously, AI studies in construction and project management predominantly consider task-specific and standalone applications instead of how to combine them with project information systems (Bento et al., 2022; Datta et al., 2024; Regona et al., 2022; Regona et al., 2023). The primary research gap is thus the paucity of system-level insights into the extent to which current PMIS environments are capable of providing AI and machine-learning capabilities in construction practice. Regona et al. (2023) explicitly identified that Future research is needed to explore the potential of embedding AI techniques into construction information management systems to support more sustainable and data-driven pro-project delivery, which is precisely the interface between AI/ML and the current pro-project information systems. Not many studies have syntactically integrated PMIS perspectives and AI readiness concepts to measure the position of PMIS in construction in relation to their potential to support AI and ML functionalities in practice.

In these regards, Finland is a country of special interest. A large number of Finnish construction organizations have already invested in digital platforms, BIM and other information management tools and work in a broader EU-wide policy environment that focuses on digitalization and data-driven decision making. To date, however, minimal empirical data exists on the perceptions of the Finnish project managers and plan-ners about the AI and machine-learning preparedness of the PMIS they are already using. So far, it has not been clear how practitioners explain the strong and weak sides of their existing PMIS regarding AI/ML, or how they imagine the integration of AI/ML capabilities into current systems and processes.

Overall, these considerations lead to the main research question of this thesis. The existing literature provides information on the use of PMIS and its limitations and data on the peculiarities of AI/ML applications in the construction industry and project management. Nevertheless, the current literature seldom examines the AI and machine-learning preparedness of up-to-date PMIS in a combined fashion. In addition, systematic knowledge on the role of PMIS in the Finnish construction projects in comparison to AI/ML both in theoretical frameworks of research and in the experience and expectations of practitioners is also lacking significantly. The thesis contains the following research problem: existing literature and practice lack a clear, empirically based understanding of AI and machine-learning preparedness of the project management information systems in the Finnish construction. The research problem is the driving force behind both RQ1 and RQ2 and four research objectives which combine to further define the position of PMIS in research and practice, to define key readiness factors and to offer a base on which future PMIS model can be built based on practitioner perception of the prevailing conditions of readiness and development. Based on the title AI and Machine-Learning Readiness of Project Management Information Systems in Finnish Construction: A Literature Review and Interview Study, the thesis thus presents the study of the AI and machine-learning readiness of PMIS based on the current research and practice in the Finnish construction to answer RQ1, RQ2 and the four objectives.

1.3 Research aim, questions and objectives

1.3.1 Objective of Study

As mentioned above, to date, PMIS within the Construction Industry are usually disjointed, often utilized to produce documentation and reporting, and incompletely linked with other significant systems like BIM and ERP. Also AI and Machine Learning are emerging in the context of particular project management and construction related tasks, but these are largely independent tools, rarely integrated into the mainstream use of PMIS. Thus, the amount of scientifically proven information on the readiness of existing PMIS to assist AI and Machine Learning in real project scenarios, specifically in Finland where digital platforms and BIM are a standard practice in Construction, is very limited.

Thus, the main concern is that research and practice are providing a restricted perspective of the association between PMIS and AI/ML. We possess some data on PMIS adoption and on AI/ML prototypes, but comparatively little on the so-cio-technical setting that would render the existing PMIS either prepared or not to add some extra AI and machine-learning capabilities. The research on organisational AI Readiness suggests that the successful adoption of AI relies on alignment of technological, organisational, and human resources and thus, the need to conduct an explicit evaluation of the current resources, capabilities, and commitment before the new solutions are introduced (Felemban et al., 2024; Jöhnk et al., 2021). To date, this evaluation has not been systematically done as far as PMIS of Finnish Construction is concerned.

Based on the discussion above, this thesis aims to assess the AI and machine-learning-readiness of project management information systems in Finnish Construction through a systematic literature review and an empirical study of project managers and planners through interviews. This research aims to develop a systemic, integrated view of the readiness of PMIS to AI and machine learn-ing by connecting the ways PMIS and AI/ML are talked about in the research world, to the way practitioners experience and build their existing systems.

1.3.2 Research Questions

To address the objective of this thesis, the research will be guided by the following two research questions:

RQ1: What is the current status of project management information systems in research and in Finnish construction practice, particularly regarding their readiness for the use of AI and machine learning?

RQ2: How do project managers and planners in Finnish construction describe the current readiness and main development needs of their project management information systems for the use of AI and machine learning?

Collectively, the two research questions will guide both the systematic literature review and the empirical interview analysis throughout the study.

1.3.3 Research Objectives

The two research questions are operationalized via four specific objectives, that collectively cover both the literature review and the empirical study:

1. To complete a systematic literature review of project management information systems and the application of AI and Machine Learning in project and construction management.
2. To document and summarize the most significant factors that characterize AI and Machine-Learning-readiness of project management information systems within the current body of research.
3. To document how project managers and planners in Finnish Construction describe the current application and readiness of their project management information systems for AI and Machine Learning.
4. To document the principal development needs and provide preliminary practical suggestions for enhancing the AI and Machine Learning-readiness of project management information systems in Finnish Construction, as a starting point for further PMIS model development in the main project.

Objectives 1 and 2 are focused on synthesizing and interpreting the existing research on PMIS, Digitalization and AI/ML in Project and Construction Management, and on establishing from this literature, a list of factors that could be used to describe AI and Machine-Learning-readiness of PMIS. Objectives 3 and 4 are focused on documenting and analysing the perceptions of project managers and planners in Finnish Construction of their current PMIS, their perception of the readiness of their PMIS for AI and ML, and their priority areas for future development.

From a methodological perspective, the systematic literature review was designed to fulfill RQ1 and to satisfy Objectives 1 and 2 by mapping how PMIS and AI/ML were addressed in the research literature, and by determining what readiness-related factors emerged from these studies. The empirical interview study was designed to satisfy RQ2 and to fulfill Objectives 3 and 4 by examining how practitioners in Finnish Construction described their PMIS, assessed their readiness for AI and ML, and identified development needs and practical recommendations. Collectively, the purpose, research questions, and objectives provide a unified framework for evaluating the AI and machine-learning-readiness of project management information systems in Finnish Construction.

1.4 Scope and delimitations

Building on the background and research problems identified in Chapters 1.1–1.3, the focus of this thesis lies in the AI and machine-learning-readiness of project management information systems (PMIS) in a specific, defined context. The scope and delimitations of this thesis are established to maintain coherence and realism in relation to the working title, research questions and objectives. The aspects of scope and delimitations are the sector, geographical location, definition of PMIS, technological focus on AI/ML-readiness, and the selected methodology. The sector scope of this thesis is limited to construction projects. The empirical aspect of this thesis is focused on building and infrastructure projects, and closely related construction work carried out by Finnish construction organizations. While other project-oriented fields such as IT, product development or generic business projects will occur during the systematic literature review, they serve to clarify how PMIS or AI/ML have been conceptualized within project management more generally, however they are not included in the empirical data. This limitation corresponds to the fact that both research questions are explicitly based in Finnish construction practice: RQ1 investigates the current status of project management information systems in research and in Finnish construction practice, while RQ2 centres on project managers and planners in Finnish construction.

Second, this thesis has a geographic focus on Finland. The empirical section of the thesis will be interviews with project managers and planners employed in the construction organizations in Finland such as major contractors and other stakeholders that have significant influence on the Finnish construction supply chain. The literature review is global in nature and uses studies of various countries and regions. Nonetheless, findings of the literature review are viewed through the prism of the regulatory, mar-ket and digitalization environment of Finland. This geography-related consideration also applies to AI/ML-readiness because the levels of digitalization and BIM-adoption of Finnish construction are rather high, among a number of companies, but the extent to which the existing PMIS is prepared to adopt AI and machine learning at the project level is poorly recorded. By concentrating on a single national context, it is possible to relate empirical observations to a shared institutional context, and, at the same time, the global research is possible in responding to RQ1 and Objectives 1-2.

This thesis defines the scope of PMIS clearly. PMIS are considered to be systems or a combination of tools that support the implementation of project planning, monitoring, controlling, and reporting in the most important areas, including schedules, costs, risks, documents and communication. This may involve project platforms to act as the main collaboration and information platform, BIM-connected project man-management systems, and integrated scheduling and document management environments which form the central project information space in construction projects. Previous research defines PMIS as project management solutions that support planning, scheduling, monitoring, control, collaboration and risk management throughout projects and portfolios (Rebuglio et al., 2025), which aligns with this operational view. Conversely, individual ERP or ac-counting systems, standalone design tools (e.g., CAD modelling software) and generic communication tools (e.g., e-mail or messaging platforms) are not defined as PMIS, but they may be interacting with PMIS and may be affected by data exchange. They are only taken into account as part of the PMIS landscape when they are an integral part of the project management information environment and are used regularly. These boundaries are required to speak about AI/ML-readiness in a narrow sense as they define where project data is developed and stored, where AI and machine learning capabilities can be implemented reasonably.

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Fourthly, there is a specified technological focus on AI and machine learning. This thesis does not develop or implement new AI or ML algorithms, nor does it create or test a new PMIS. The technological focus of the thesis concerns the conditions under which AI/ML capabilities could be integrated into currently available PMIS in Finnish construction. Examples of such include the availability and quality of project data, the degree of system integration, the flexibility of the architectures of current PMIS, and the existence of interfaces or processes that could support AI-based prediction, classification or automated analysis. Organisational AI-readiness research indicates that the successful implementation of AI depends on the alignment of technological, organisational and human capabilities, and an informed evaluation of whether the existing resources and processes meet the requirements of the intended AI application (Felemban et al., 2024; Jöhnk et al., 2021). The idea of these concepts was applied to PMIS in construction projects in this thesis , with consideration to how current systems and practices can either enable or hinder future use of AI/ML.

The methodological coverage of the thesis includes a systematic literature review and semi-structured interviews. The systematic literature review deals with project management information systems and the use of AI and machine learning in project and construction management, in accordance with Objectives 1 and 2. The systematic literature review summarizes how PMIS and AI/ML have been treated in the past literature and presents factors that can be construed as characterising AI and machine-learning-readiness of PMIS. Objectives 3 and 4 will involve the empirical part of the thesis: semi-structured interviews with planners and project managers of Finnish construction organisations. The interview study is qualitative in terms of scope and seeks to realise the in-depth descriptions of how the practitioners use their PMIS, their perceptions of the AI/ML-readiness of the systems, and the development needs and practical recommendations they derive. The literature review will be focused on RQ1 and Objectives 1-2, and the interview study will be focused on RQ2 and Objectives 3-4. Thus, the empirical findings cannot be statistically extrapolated to other settings not related to the Finnish construction setting, but they do give very insightful contextual information about AI and machine-learning-readiness of PMIS within this setting.

In total, the above mentioned sectorial, geographical, system, technological and methodological delimitations establish a focused yet sufficiently rich setting for evaluating the AI and machine-learning-readiness of project management information systems in Finnish construction, as defined in the thesis title, research questions and objectives.

1.5 Key concepts and working definitions

This section defines the key concepts used in the thesis. The definitions are provided to ensure consistent use of concepts related to PMIS, AI, machine learning, and readiness in the context of Finnish construction. Chapter two will give a full theoretical discussion and literature review on these topics.

Project Management Information Systems (PMIS)

A Project Management Information System is an electronic system, or a set of systems, that supports the planning, monitoring, control, and reporting of projects by storing, processing and presenting the project related information. Typical examples of project information that might be stored, processed and displayed within a PMIS are a schedule of a project, cost data, risks, issues, scope of work changes, documentation, stakeholder communication and in the case of construction projects, links to models like Building Information Modelling (BIM). Past studies have established that PMIS offer a variety of advantages to individual project as well as portfolio level project teams such as aiding in planning, scheduling, monitoring, controlling, collaborating, and risk management (Rebuglio et al., 2025). In the case of AI and machine-learning preparedness of PMIS, they are perceived as the digital core of project information, the place where most of the relevant project information is typically generated and maintained and would therefore be the main origin of augmenting AI/ML functionality into the regular workflows of a project team.

Machine Learning and Artificial Intelligence

To address this thesis, artificial intelligence and machine learning will be de-fined in practical and application-oriented terms, which are relevant to project and construction management. To use them in the context of this thesis, artificial intelligence and machine learning will be called data-driven computational techniques capable of finding patterns in data to help or automate processes like prediction, classification, optimization, and natural language processing. Applications of AI and ML in the construction and project management industries are being increasingly evidenced, with some showing greater accuracy and/or efficiency than traditional methodologies (Bento et al., 2022; Datta et al., 2024). The present thesis focuses on narrow, domain-specific AI/ML applications that can be integrated into PMIS, rather than on broader definitions of artificial intelligence. The main focus of this thesis is the interaction of AI/ML with project data and processes, which are handled in PMIS within the Finnish construction sector.

Readiness

In this thesis, readiness refers to the extent to which PMIS and their organisational context are prepared to utilise and support AI and machine-learning capabilities. The concept of readiness is used as a working concept to describe a socio-technical state, which has multiple, interdependent aspects. Technically, the readiness comprises of availability, quality, structure and interoperability of project data, flexibility and integration of system architecture. At the organizational level, readiness covers aspects like positions, capabilities, resources, and changeability that influence the ability to plan, implement, and sustain the functionality of AI/ML in practice. At the human level, preparedness has an impact on the attitude, trust, perceived utility, and readiness of users to utilize the AI-supported tools. From a governance perspective, readiness includes regulations, responsibilities, risk-management practices, and alignment with organisational strategy and data-use ethics. Studies have shown that a systematic evaluation of these dimensions can enhance the chances of successful AI deployment and help organizations match their AI ambitions with capabilities (Felemban et al., 2024; Jöhnk et al., 2021). The preparedness concept is a bridging concept between the current PMIS environments and the potential application of AI/ML in the construction projects in Finland.

AI-enhanced PMIS

This thesis used the term AI-enhanced PMIS to refer to a hypothetical future state where project management information systems can perform AI and machine-learning functionality as a normal aspect of their operation. Examples of AI-enhanced PMIS include PMIS that provide predictive forecasting of schedule or cost out-comes, automatically rank risks and issues, or PMIS that are AI-assisted in analysis and categorization of documents and site information. There is no presumption that AI-enhanced PMIS are prevalent in the Finnish construction industry now, but rather, it is likely to develop over time. Thus, the empirical and literature-based research of the present the-sis was dedicated to the extent to which the existing PMIS and the organizational contexts in which they are implemented are ready to introduce AI/ML improvements.

The working definitions of PMIS, artificial intelligence and machine learning, readiness, and AI-enhanced PMIS together provide a consistent conceptual framework for assessing the readiness of project management information systems in Finnish construction for AI and machine-learning applications.

1.6 Structure of the thesis

This section outlines the structure of the thesis. The second part of the thesis includes the chapters organized so as to answer the two research questions and to fulfill the four research objectives related to the AI and machine-learning readiness of the project management information systems in Finnish construction.

Chapter 1, Introduction, represents the general subject matter and context of the AI and machine-learning readiness of PMIS in Finnish construction. In addition to presenting the background and motivation (Section 1.1), the research problem and research gap (Section 1.2), the research objective, question and objectives (Section 1.3) and the limits and range of the study (Section 1.4), the final Section 1.6 also includes descriptions of how the other parts of the thesis are organized to address RQ1 and RQ2 and to achieve the four research objectives.

Chapter 2 provides the theoretical framework and the systematic literature review. It reviews prior research on project management information systems, digitalization and the use of AI and machine learning in project and construction management. Chapter 2 develops the concept of AI and machine-learning readiness of PMIS and identifies factors that explain this readiness according to previous studies. Therefore, Chapter 2 contributes mainly to answer RQ1 and to realize Objectives 1 and 2 by explaining the way that PMIS and AI/ML are handled in the literature and by synthesizing the dimensions of readiness.

Chapter 3 presents the methodology of the research. It explains the total design of the research and it specifies the details of the systematic literature review, the design of the semi-structured interviews, the processes of collecting and analysing the data, and the ethical considerations of the study. Chapter 3 shows how the selected methodologies align with RQ1 and RQ2 and with the four research objectives and how they altogether support an integrated analysis of the AI/ML readiness of PMIS in the Finnish construction industry.

Chapter 4 contains the results obtained through the systematic literature review and the empirical interview study. It describes the factors related to the AI and machine-learning readiness of PMIS found in the literature and the perceptions of Finnish project managers and planners concerning the current utilization, the readiness and the developmental needs of their PMIS. Chapter 4 is structured based on the two research questions and the dimensions of readiness and it presents the complementary points of view of research and practices. Chapter 5 presents the discussion and the conclusions. It interprets the findings in relation to the theoretical framework, it indicates the consequences for the development of PMIS and the introduction of AI/ML in the Finnish construction, it indicates the practical proposals and key developmental needs, it considers the limitations of the study and it proposes the directions of the further research.

In total, this organization of the thesis establishes a rational and consistent sequence of studying the AI and machine-learning readiness of the project management information systems in the Finnish construction in accordance with the title of the thesis, RQ1, RQ2 and the four research objectives.

2 Literature review

Chapter 1 has characterized the rationale of AI and machine-learning maturity of project management information systems as a topical issue to Finnish construction: projects are information-intensive, PMIS are a core, although disjointed, digital core, and AI/ML applications are being presented as a non-integrated toolkit, whose use in day-to-day project management is uncertain. It is on this motivation that chapter 2 is founded, establishing the theoretical and conceptual underpinnings needed to go about this preparedness in a systematic way. The chapter has summarised past re-search on PMIS, AI and machine learning in project and construction management, organisational and socio-technical solution to AI adoption and data, technical and governance requirement of AI-enabled project information system. Regarding RQ1 and Objectives 1-2, the discussion will be based on how the existing literature de-scribes the present situation with PMIS and what aspects determine their AI/ML read-iness and prepares the way to the empirical research of the Finnish construction prac-tice according to RQ2.

The chapter starts with the roots of PMIS and continues to a multi-dimensional concetualisation of AI/ML preparedness at the PMIS level. Section 2.1 presents a conceptualisation and an understanding of definition of PMIS in project-based organisation particularly construction. It touches on basic functions and structures of PMIS and their application in the construction project management. Section 2.2 further explains the application of AI and machine-learning in project and construction management, and outlines where AI has been applied in project man-management knowledge areas. Section 2.3 addresses AI/ML applications in construction project management and the emphasis on model-level-studies and task-specific tools today. Together, these sections render PMIS the main digital environment where project data are generated and handled and AI/ML an emerging set of approaches that, hypothetically, can be included in these environments.

Section 2.4 continues with organisational preparedness and uptake. It is based on generic AI preparedness frameworks, as well as construction-specific research on digitalisation to show that successful implementation of AI needs to align technological, organisational and human potentials, and it is a condition of institutional and cultural contexts. It is possible to think of PMIS as socio-technical systems in which tools, data formats, processes and roles are all linked together to promote the idea that AI/ML preparedness cannot be reduced to technical standards. This is further elaborated in section 2.5 which examines data and technical preparedness to AI/ML-enabled PMIS, distinguishing between structured project data (such as BIM/IFC, schedules and cost records) and unstructured or semi-structured data (such as specifications, contracts and safety reports). It is a synthesis of the evidence on the integration of BIM with AI, data standards, document-based AI and system architecture to attract concrete data and technical impacts that can define whether information managed with PMIS can be utilized by AI and machine learning.

Section 2.6 is followed by the emphasis on governance, trust and change management in which AI/ML-enabled PMIS can only be consumed and appreciated when stakeholders believe in the outputs, how they are generated and feel that there are obvious responsibilities and safeguards available. It brings together the literature on trustworthy AI, ethics, data management, capacity building and human-AI interaction in a way that shows that preparedness also implies lifetime-inspired governance practices, education, AI literacy and empowering organisational climates. Section 2.7 links these strands to project and PMIS success by asserting that AI/ML readiness is only pertinent in the sense that AI-enhanced PMIS can be used to assist in supporting the already established success measures: time, cost, quality, safety, transparency and user satisfaction, and summing up the previously existing evidence of AI/ML impact on project and project-management performance.

Lastly, Section 2.8 summarises the literature by outlining the main themes and pin-points research gaps and a working conceptualisation of AI and machine-learning preparedness of PMIS. This conceptualisation is formulated as a multi-dimensional concept that integrates five aspects that are interrelated: the organisational environment of AI/ML in PMIS, the technical and integration capacity of PMIS and related systems, the availability and structure of project and document data, governance and trust arrangements including change management, and the alignment of AI/ML functionality with project and

PMIS-related success. These dimensions give a consistent view through which to understand the available research in the context of RQ1 and are sensitizing ideas of the empirical research in RQ2. By doing this, Chapter 2 satisfies Objectives 1 and 2 and provides the conceptual basis of the research design in Chapter 3 and the Finnish construction practice in Chapter 4.

2.1 Project Management Information Systems in project-based organisations

2.1.1 Definitions and conceptualisations of PMIS

The key concept in this thesis is project management information systems, but the term has a variety of, partly overlapping, uses in literature. Other writers define PMIS as more of software applications or toolsets to aid project management processes including planning, scheduling and reporting, with an emphasis on the technological artefact and its capabilities. Others treat PMIS as information systems or infrastructures that receive, store, and share project-related information or data across organisational boundaries, emphasising integration, communication and decision-support functions, but not individual software packages (Rebuglio et al., 2025; Monteiro et al., 2025).

In this continuum, there is one line of work that views PMIS as project management software intended to help project managers to plan the activities, manage resources and monitor progress of individual projects or portfolios. The system provides work breakdown structure modules or features, Gantt charts, resource allocation features, time sheets and issue logs. In this regard, PMIS are described as assisting in a variety of purposes, which include supporting planning, scheduling, monitoring, control, collaboration and risk management in projects and portfolios (Rebuglio et al., 2025). Bento et al. (2022) touch upon the role of AI in project management as being conditional upon the project-specific data that is stored in project management information systems and other tools, which supports the notion that PMIS constitute a crucial digital environment of data collection as opposed to a distinct AI artefact.

A second set of authors conceptualizes PMIS as central information systems that are used to mediate information flows among stakeholders and across project phases. In this case, functionality is not the only important input of PMIS, but also the ability to combine various data sources, and deliver timely, dependable information to make decisions at project, programme and portfolio levels (Rebuglio et al., 2025). Zabala-Vargas et al. (2023) emphasize that the architecture, engineering and construction sector is a rather information-intensive project management, where huge amounts of data are produced, the quality and structure of which are becoming more difficult to control. PMIS are thus conceptualised as being part of larger information infrastructures that coordinate information between organisations, as opposed to discrete software products.

A third body of work integrates PMIS into project management and organisational structures. In this perspective, PMIS are interwoven with project management offices (PMOs), reporting mechanisms and performance management procedures. Monteiro et al. (2025) compare the presence of both PMIS and a PMO with more professionalised project management structures, finding that the use of PMIS has a positive and significant impact on the performance of project managers, which supports the significance of these systems as tools to support project management operations and decision-making. This conceptualisation, which is more governance-focused, emphasizes PMIS as components of a socio-technical system that influences the standardization of project information and its interpretation and utilization in decision-making, as opposed to technical tools.

Although there have been such diverse views, the literature has converged to hold that there are disjointed terminology and conceptual boundaries surrounding PMIS. According to Rebuglio et al. (2025), the former is associated with nomenclature: the majority of sources mention this type of software as Project Management Information System (PMIS), followed by Project Management Software (PMS), Project Management System, and Project Management Tools. Such a deficiency of a single terminology leads to a problem of comparing the studies and makes the mapping of specific findings to a particular type of systems more complicated. Simultaneously, it indicates the variety of PMIS solutions in practice, both generic project tools and complex and integrated information environments.

In this disjointed terminology, however, there is a definite common centre. Majority of the definitions emphasize that PMIS aid project planning and control along major dimensions including time, cost, scope and risk, and are central repositories and processing centres of project information (Rebuglio et al., 2025; van Besouw and Bond-Barnard (2021)). They are supposed to offer current perspectives on project status, assist coordination and collaboration among all the stakeholders, and enable monitoring and reporting at various organisational levels. PMIS in project-based organisations are thus regarded as a component of the digital infrastructure that makes the repeatability of processes and some standardisation of project management practises possible.

A continuation of these strands, the thesis takes a working understanding of PMIS that aligns with the main concepts presented in Section 1.5. PMIS are perceived as electronic systems, or a combination of electronic systems, which assist project planning, monitoring, control and reporting through the storage, processing and presentation of project-related data. They include single applications and more advanced, integrated environments that integrate scheduling, cost, risk, document and communication capabilities (Rebuglio et al., 2025). The given working view is consistent with the premise that in general, PMIS enhances the efficiency and digitalization of project-based businesses, as well as streamlines planning, scheduling, teamwork, and efficient task assignment (Rebuglio et al., 2025). It also offers a direct connection to AI and machine-learning preparedness: since AI/ML applications in project and construction management will be based on historical and real-time project data (Abioye et al., 2021; Datta et al., 2024), PMIS form a prime location where such data would be produced, stored and accessed and where AI/ML capabilities would be realistically implemented in Finnish construction practice under RQ1.

2.1.2 Core functions and architectures of PMIS

In addition to definitions, one should understand the actual activities of PMIS and how they are set up in project-based organisations. In the literature, it is always known to have a set of the main functions which PMIS should support. They are time and schedule management (e.g., activity planning, baseline schedules and progress tracking), cost and budget management (e.g., cost codes, forecasts and earned value), and risk, issues and change management with structured registers and workflows (Rebuglio et al., 2025; Bento et al., 2022). Most PMIS also include resource planning modules, contract and procurement information modules and other types of status and milestone reporting, which are consumed by project and portfolio reviews.

Another key activity of most PMIS, particularly engineering and construction projects, is document and drawing management. Systems are supposed to store and manage versions of specifications, drawings, models, change orders and correspondence all of which frequently have formal approval procedures and audit trails. The elements of communication and collaboration, such as the simplest comment boxes to the more sophisticated integrated messaging, task discussions and notifications are often embedded in PMIS or closely coupled services. Then, Dashboards and reporting features compile schedule, cost, risk and document data as key performance indicators, charts and exception lists that aid managerial control and early detection of problems (van Besouw & Bond-Barnard, 2021).

These functions create and analyze huge amounts of information. Zabala-Vargas et al. (2023) emphasise that the sheer amount and diversity of information generated by project management has become a challenge to organisations, which has led to interest in big data, data science and AI as methods to derive value out of project information. According to Jahanger et al. (2021), construction projects produce a lot of information at the construction stage, but much information remains handled with disjointed, paper-based or semi-digital systems. Datta et al. (2024) also note that AI/ML uses in the construction field are starting to rely more on data created throughout the project lifecycle. The manner in which PMIS gather, organize and deliver data, as structured fields, semi-structured logs or unstructured documents, therefore, directly affects the viability of AI/ML application.

The architectures which implement these functions differ significantly. Other organisations have one, combined project platform, which encompasses a wide range of activities, including planning to document control and reporting. Some employ a set of dedicated tools, e.g. a scheduling application, a distinct cost management system, a specific document management platform, and other tools to manage risk registers or site reporting, but they are not fully or even partially linked. Architectures may be on-premises, cloud-based, or hybrid, and web-based can be used as an essential component of a distributed project environment (van Besouw and Bond-Barnard, 2021; Regona et al., 2023). With the increasing complexity of projects, the adoption of advanced Project Management Information System (PMIS) technologies to enhance efficiency and quality in projects is required, which further amplifies the significance of systems architecture and integration (van Besouw and Bond-Barnard, 2021).

PMIS architectures commonly are interconnected with other enterprise and technical systems in construction and infrastructure projects. Integrations with finance systems or Enterprise Resource Planning (ERP) provide an opportunity to align the data on project costs with corporate accounting. Linkages to time tracking systems, site reporting software and field management software introduce close to real-time data on the construction site into the project information environment. Coupling with Building Information Modelling (BIM) software, via model viewers, metadata connections or shared data environments, expands PMIS out of the conventional document and schedule management into model-based information spaces (Pan & Zhang, 2021; Regona et al., 2023). Simultaneously, some of the studies indicate that even with the popularization of digital tools, there is fragmented data and lack of integration between such systems (van Besouw and Bond-Barnard, 2021; Regona et al., 2023).

As it has been shown, proper utilisation of PMIS and associated architectures can enhance the project performance and enable greater digitalisation. As Monteiro et al. (2025) demonstrate, the use of PMISs positively and significantly impacts the performance of project managers, which confirms the significance of these systems as tools that facilitate project management processes and decision-making. Jahanger et al. (2021) show that when the data structures and integrations are established, the digitalisation of construction-phase information management can enhance transparency and control among the project owners. According to Chen et al. (2025), the concept of digital transformation in project management is associated with rearranging processes and positioning around digital platforms, such as PMIS, to enable the use of more data to make decisions.

Through an AI/ML preparedness lens, these functions and architectures are important since they determine the data landscape and determine the possible points of insertion of AI/ML capabilities. The quantity, size and quality of data presented in PMIS, the level of integration between tools and platforms, and the representation of workflows defines which AI/ML use cases can be technically and organisationally viable. Here are intersected by technical AI readiness factors, including interoperable information systems and high-quality data (Felemban et al., 2024), and organisational readiness factors, including governance of digital platforms and ability to adjust processes around new types of decision support (Jöhnk et al., 2021). Stated differently, PMIS functions and architectures either permit or preclude the direction towards AI-enhanced project management, and awareness of this position within construction projects is a requisite stage in responding to RQ1 in the Finnish context.

2.1.3 PMIS in construction project management

Although PMIS is applicable in most project-based fields, the application in the construction project management has its peculiar features that can be directly applied to this thesis. Construction projects are usually characterised by a number of organisations, complicated contractual frameworks and extensive information sharing throughout the construction process. PMIS here can be in the form of project web platforms, common data environment or project extranets, which can be a shared collaboration space between clients, contractors, designers and other stakeholders. These systems are integrated document management, communication, workflows and in some cases simple schedule and cost data. Moreover, construction project organisations apply a variety of BIM-related tools and field applications which are less or more connected to the underlying PMIS (Pan and Zhang, 2021; Jahanger et al., 2021).

A number of studies report on the benefits that the digitalisation of the construction-phase information management using PMIS or similar platforms has. Jahanger et al. (2021) state that the transition to more integrated digital processes (as opposed to fragmented, paper-based or semi-digitized ones) can give the project owners a greater level of transparency, a more comprehensive picture of the project performance and a more dependable set of records to use in making decisions and resolving disputes. According to Rebuglio et al. (2025), the implementation of PMIS in construction projects has been linked to increased compliance with time and budget constraints. As Regona et al. (2023) remark, with the growth of AI use in construction, digital platforms and project information systems grow in importance as the environments in which data to be used in AI applications is created and stored.

The regulatory and client-driven information needs also influence construction-specific PMIS usage. Digital models, drawings, inspection records, quality documents and site diaries are often maintained in or in close relation to PMIS, occasionally in accordance with the information needs of owners and national guidelines. As Datta et al. (2024) and Abioye et al. (2021) point out, AI/ML applications in the construction sector are based on the data created at various stages and systems, such as schedule, cost, quality and safety data. The success of such applications is determined by the consistency and systematization of such information in PMIS and other tools and whether the digital processes are strong enough to enable the repetition of data retrieval and analysis.

Simultaneously, constraints and obstacles in the use of PMIS in construction are actively documented. Regona et al. (2023) note that a significant number of construction organisations do not have well-developed digital infrastructures and integrated information systems, which hinders access to data needed to apply AI applications, including data collection, storage and analysis. Van Besouw and Bond-Barnard (2021) underline fragmentation of project data, which is spread across various systems, and the challenges it poses to overall monitoring of project performance and smart PMIS architectures. According to Regona et al. (2022), high cost, insufficient top-down support and untrained workers are the barriers to implementing AI across more areas of the built environment sector, which means that despite the availability of PMIS, their more sophisticated capabilities might go to waste.

The other common thread is that existing PMIS in the construction sector tend to be utilized mostly as documentation and compliance systems and not as advanced decision support systems. According to Datta et al. (2024) and Abioye et al. (2021) most uses of AI/ML in the construction sector are currently stand-alone prototypes or task-specific applications, such as in cost estimation, scheduling or safety monitoring, but have not yet been integrated with enterprise information systems and project platforms. Similar to Chen et al. (2025), digital transformation projects in project management often have difficulty with the lack of alignment between digital technology and current project activities that may result in partial or uneven utilization of PMIS capabilities, including analytics.

To conduct the assessments of AI and machine-learning preparedness under RQ1, these strengths and weaknesses of PMIS in construction project management are the beginning point. On the one hand, PMIS make available common digital areas, traceable information flows and systematized documentation that would be able to support data-driven and AI-enhanced project management in Finnish construction. Conversely, problems like disjointed tool scenery, imbalanced integration, inconsistent usage customs, data quality issues and restricted organisational competencies indicate gaps in readiness that must be learned systematically. Such gaps are directly correlated with AI readiness factors that can be identified at organisational level, such as technological infrastructure, data quality, skills and governance (Felemban et al., 2024; Jöhnk et al., 2021) and drive the subsequent conceptual and empirical investigation of AI and machine-learning readiness of PMIS in Finnish construction practice.

2.2 AI and machine learning in project and construction management

The foregoing section described PMIS as central digital platforms which gather, organize and share project data throughout planning, execution and control. It is on this background that AI and machine learning are being marketed as technologies capable of analysing these data and enhancing project decision-making. In general project management literature, the authors state that due to the rapid development of artificial intelligence (AI) and AI technologies, the project management has undergone change in various forms, AI has transformed the aspects of projects in the planning, execution, and monitoring/control stages, as well as presented new challenges and complexities (Bachari et al., 2025). On the techniques side, AI techniques like machine learning, deep learning, and hybrid models have demonstrated their ability to improve PM techniques at all stages of a project, including planning, execution, and monitoring (Adamantiadou and Tsironis, 2025).

Meanwhile, the literature on construction management reports a gradual yet consistent digital transformation, with AI and ML methods being considered to be actively investigated throughout the project lifecycle in order to improve the decision-making process and productivity (Datta et al., 2024) and mentions that with the growing amount of data being generated at all stages of the building lifecycle and the appearance of other digital technologies, AI can tap into them and leverage the capabilities of other These trends directly apply to the PMIS in Finnish construction: they imply an increased catalogue of AI/ML applications that rely on project data that are usually stored in PMIS or other systems, and they also put the question of whether existing PMIS architectures and data and organisational conditions are prepared to support such applications (RQ1, Objectives 1-2).

The rest of this section initially scans AI/ML applications in generic project management knowledge areas (Section 2.2.1) and then more specific to applications in construction project management (Section 2.2.2). A combination of these subsections forms the foundation of further investigation of how PMIS in Finnish construction may realistically support and host such applications and what AI/ML preparedness may imply at PMIS level.

2.2.1 AI/ML applications across project management knowledge areas

According to a developing array of reviews and empirical research, AI represents a cross-cutting trend that influences various areas of project management knowledge instead of a niche. Systematic reviews highlight that artificial intelligence is projected to change project management in the coming years, in terms of how projects are planned, monitored and controlled in all areas of knowledge, and that AI methods like machine learning, deep learning and hybrid models have demonstrated their potential to improve PM methods through all the phases of project, including planning, execution and monitoring (Nenni et al., 2025), and that AI techniques, including machine learning, deep learning and Bachari et al. (2025) clearly align AI applications with the PMBOK framework, indicating that their research is intended to discover AI methods, tools, approaches, models and frameworks to each of the project management knowledge areas presented by PMBoK. On the same note, Fridgeirsson et al. (2023) construct their empirical instrument in a way that the questionnaire is modelled based on 49 processes of the 10 project management knowledge areas and the questionnaire consists of 53 items. The given endeavors warrant the application of PMBOK knowledge areas and processes as the prism through which AI/ML applications should be organized and, consequently, the PMIS modules and data structures that are the most applicable to AI/ML preparedness can be viewed.

In this literature, there are many knowledge areas that come out to be points of focus. Numerous reviews find that the body of literature on AI in project management remains somewhat limited and disjointed, with most of the research focusing on particular functions (scheduling, risk analysis and cost forecasting) (Bento et al., 2022). Nenni et al.

(2025) also indicate that the present uses of AI in project management are focused on risk management, forecasting, and scheduling, and other knowledge areas like risk stakeholder engagement or procurement are barely addressed. Zabala-Vargas et al. (2023) offer a complementary view by demonstrating that in the AEC industry the most utilised areas of knowledge by emerging technologies are Cost, Quality, Time, and Scope and that research in this field is heavily quantitative in nature. Collectively, these results suggest that AI/ML progress until now has been concentrated on the more information-intensive control activities of project management that are more directly aligned with core PMIS modules of schedule, cost, risk, scope and quality.

Time Management and Scheduling

One of the most evident application areas is time management and scheduling. The survey-based research reveals that the surveyed experts have also identified three main fields in which AI influences efficiency, accuracy, and decision-making in project management: data collection and reporting, performance monitoring, and project time management and scheduling (Müller et al., 2024). Much of the AI applied in this field is based on past schedule baseline data, activity characteristics and progress reporting to forecast delays, approximate remaining time or recommend re-sequencing opportunities. Algorithmically, it can be seen that hybrid AI models are more effective at risk assessment, duration prediction, and cost estimation (Adamantiadou and Tsironis, 2025), implying that predictions related to schedules tend to overlap with cost and risk modelling. Summarising the overall rationale, Lai et al. (2025) note that AI can aid in project management by improving the accuracy of predictions, increasing the processing speed, and making decisions based on data.

The applications in PMIS terms are very dependent on the completeness and granularity of schedule information: activity codes, dependencies, progress measurements and change histories in scheduling modules or associated tools. Hughes et al. (2025) highlight that AI can automate project routine management tasks, improve data accuracy and provide predictive analytics to aid in proactive decision-making, which, over the context of a PMIS, would mean automated schedule updating, anomaly detection in progress data, and predictive warnings on dashboards. Unless PMIS implemented in Finnish construction are able to represent schedule baselines, updates and change rationales in a uniform, machine-readable manner, their ability to accommodate such AI/ML functionality will be restricted even with appropriate algorithms in place.

Cost Forecasting and Risk Management

The second big group of AI/ML applications is in cost management and risk management. Cost is cited by Zabala-Vargas et al. (2023) as one of the most common areas of application of big data, data science and AI, whereas Nenni et al. (2025) directly mention risk management and forecasting (as a rule, including cost variables) as the most popular topics. Common uses include forecasting cost increases, estimating contingency requirements or prioritizing risks by using historical project attributes and performance. According to the reviews, machine learning models have potential in predicting performance indicators of a project, although many of them are at the stage of proof-of-concept (Bento et al., 2022), which reflects the potential and the current level of maturity of most models.

From a PMIS perspective, these models depend on structured cost data—such as budgets, cost codes, committed and actual costs—and on systematic risk register information. According to Müller et al. (2024), the influence of AI on the areas of data collection and reporting and performance monitoring is core, which, in practice, would necessitate PMIS to record cost and risk information in a detailed manner and connect them with schedule and scope items. When these linkages are loose or in a variety of unintegrated systems, AI/ML preparedness will be low despite research showing high predictive accuracy on curated datasets.

Quality, Scope, Safety and Other Knowledge Areas

In addition to time, cost and risk, AI/ML has been utilized in quality and scope-related processes, albeit to a smaller degree. According to Zabala-Vargas et al. (2023), such knowledge areas as Quality and Scope are some of the areas where new technologies are applied, such as detecting defects, non-conformance analysis or requirement classification. Salimimoghadam et al. (2025) discover that AI has a transformative impact on the accuracy of the forecast, mitigation of risks, collaboration with stakeholders and management of safety and deals with issues like integration with legacy systems, data quality, and resistance to change. It means that AI is already entering the sphere of stakeholders and communication, although it is mostly via analytics of already available performance and safety data.

Natural language and generative models are used more and more in communication and applications related to stakeholders. According to a report by Felicetti et al. (2024), the paper under consideration discusses the adoption and adaptation of these tools by project managers with a particular focus on ChatGPT, as the latter are starting to be used by project managers to draft communications, summarise texts or discuss alternatives. Such tools may be incorporated in the form of conversational interfaces over project repositories in the context of PMIS, but in this case, underlying PMIS data and documents must be available over APIs and suitable governance must exist.

Reporting, monitoring and data-driven decision support

Some of the studies note how AI can be used to transform increasing amounts of project data into actionable information. Zabala-Vargas et al. (2023) emphasize that the fact that the algorithms are able to process a lot of data and extract valuable information is one of the advantages of artificial intelligence in project management which allows project managers to make informed decisions and modify the planning and allocation of resources in real time. Müller et al. (2024) also focus on the significance of such spheres as data collection and reporting and performance monitoring as the main directions in which AI enhances efficiency and the quality of decisions.

These functions are interrelated with PMIS dashboards and reporting modules. As noticed by Almeida et al. (2025), projects management is becoming digital-friendly, and even AI-based applications are being developed to help in planning, controlling, and monitoring project performance. Regona et al. (2023) further note that the growing access to digital project information opens possibilities of higher-order analytics and AI-driven insights. In practice it is natural that PMIS that centralize schedule, cost, risk and document information into consistent data models will be the natural location of AI-based monitoring capabilities like predictive key performance indicators, automated exception reports or anomaly detection in time-cost performance. In a summary, Lai et al. (2025) describe the motivation that AI increases the accuracy of predictions, their processing speed, and more data-driven decisions, which are exactly the features that are anticipated of high-quality PMIS analytics.

Simultaneously, the current studies emphasize the lack of fragmentation and integration with project information systems. Bento et al. (2022) refer to the overall AI-in-PM literature as comparatively small and fragmented, and Regona et al. (2023) observe that most AI applications are shown as one-off prototypes, rather than being incorporated as the solution into project information systems. Where AI-powered dashboards or assistants are shown, they frequently use customized datasets, instead of real-time PMIS data feeds. This implies that AI capabilities are around PMIS in a number of organisations, and not an integral component of them.

Implications for AI/ML Readiness of PMIS

Throughout these knowledge areas, there are general trends that can be applied directly to AI/ML preparedness of PMIS. To begin with, AI studies and initial applications are focused on data-intensive control functions (schedule, cost, risk, performance monitoring), where PMIS already dominate the storage and aggregation of information (Bento et al., 2022; Nenni et al., 2025; Zabala-Vargas et al., 2023). Second, prediction accuracy, processing speed and data-driven decisions are defined as the value proposition of AI in (Lai et al., 2025; Zabala-Vargas et al., 2023) which assumes that PMIS data are complete, structured and available enough. Third, most of the available literature is at the proof-of-concept stage and has not yet been integrated into PMIS (Bento et al., 2022; Regona et al., 2023).

These notes confirm a perception of AI-intelligent PMIS whereby schedule, cost, risk and reporting modules deliver quality interoperable data and where AI services can be incorporated into current workflows as opposed to stand-alone tools. Even they refer outside of technical questions. According to Hughes et al. (2025), AI enables project managers to concentrate on more advanced activities because of automating routine administrative activities, which means that the roles and competencies are going to change as AI capabilities become integrated into PMIS. On a larger scale, project environment adoption of AI involves matching the capabilities of technologies, organisational processes, and human factors (Yang et al., 2025). In the case of Finnish construction, this implies that the readiness of AI/ML of PMIS as assessed based on RQ1 should involve not only the presence of proper data in the systems to be used in schedule, cost, risk and reporting applications, but also the feasibility of organisational processes and user practices to accommodate AI-augmented decision-making in these spheres.

2.3 AI/ML applications in construction project management

Once narrowed down to generic project management, AI and ML applications are closely connected to the specifics of construction projects: physical manufacturing on temporary grounds, heavy subcontracting, close reliance on design and BIM data, and the heavy exchange of information throughout the construction process. The asymmetric developments and the issues of opportunity are pointed out in literature reviews. As Datta et al. (2024) point out, the construction sector is now lagging, but all project life stages are actively being digitalized and, in this respect, AI, and ML techniques are under investigation to enhance decision-making and productivity. Lai et al. (2025) also express that as artificial intelligence (AI) and Industry 4.0 continues to expand, construction management has entered a period of fast digital transformation, but state that only 60 articles fit their inclusion criteria regarding AI in construction management, and in particular, schedule management, cost management, quality management, and health and safe-ty management.

However, thanks to this rather sparse literature, AI techniques have already been applied in a vastly diverse range of construction industries. According to Chen et al. (2025), the use of AI techniques in the construction of infrastructure (earthworks, tunnelling, pavement construction, and bridge engineering) has been on the rise over the last ten years. Pan and Zhang (2021) define six of the so-called hot research topics in construction engineering and management knowledge representation and reasoning, Information fusion, computer vision, natural language processing, intelligences optimisation and process mining, which shows that AI is be-ing pursued in both numeric and textual data. But a number of reviews all come to a common limitation: according to our review, the majority of AI and ML applications in construction projects are considered independent tasks, to count cost, timeline, and safety, and few studies have been performed to study integrated lifecycle decision support (Datta et al., 2024). Datta et al. (2024) also add that a clear knowledge gap in the organized categorization of the application of these technologies in the various phases of the construction project life cycle remains, and the current application of AI is rather fragmented and task specific.

Cost Estimation and Forecasting, Scheduling and Planning

According to the general trends in project management, several AI-based applications related to construction are engaged in estimating costs, forecasting project productivity, and planning schedules. Lai et al. (2025) demonstrate that AI dominance in construction management is particularly high in the following areas: schedule management, cost management, quality management and health and safety management. On the cost side, bid prices, cost overruns or unit rate are predicted with machine-learning models based on historical project data, although, as Bento et al. (2022) note in a wider project management context, machine learning models show promise in predicting project performance indicators, although most are still in proof-of-concept phase.

BIM is frequently used in conjunction with AI in scheduling and planning applications. As an illustration, there is this paper, which outlines a blueprint to create construction schedules using machine learning methods, combined with building information modelling (BIM) data (Al-Sinan et al., 2024). The suggested framework uses historical project schedules and BIM models to train machine learning models that could predict the durations of activities and the order of activities (Al-Sinan et al., 2024), and case-study findings indicate that the ML-BIM approach could create viable schedules comparable in quality to those created by the experienced planners, and it could also save a lot of time on the manual effort. The BIM-AI literature discusses the same opinions more generally, explaining BIM as a central repository of information, whose structured data could be analysed by AI to optimise scheduling, resource allocation, cost estimation, and risk prediction (Rane, 2023).

Nonetheless, these technical demonstrations have strong data and integration limitations. According to Al-Sinan et al. (2024), the implementation of the framework is limited by the quality and accessibility of BIM data, the standardisation of activity definitions, and integration of ML tools with current project management information systems. Likewise, Pan and Zhang (2021) note that BIM-integrated platforms are providing a richer data space to be automated and AI enabled, albeit not uniformly across construction projects. Du et al. (2024) describe BIM/IFC data readiness to AI as only at an intermediate level and underline that the ways to effectively convert data in BIM formats, including Industry Foundation Classes (IFC), in formats that can be used by AI applications, remain to be investigated. In the case of PMIS in Finnish construction, the findings suggest that AI-enhanced scheduling and cost applications will not only be based on the presence of BIM, schedule and cost modules, but also on the quality, standardisation and interoperability of data across PMIS, BIM environments and ERP systems.

Safety, Quality and Risk Management

Safety and risk man-management is another important area of AI/ML application in construction. Regona et al. (2023) prove that the problems of safety management, productivity enhancement, and cost and schedule optimisation were the leading ones in the field of AI research in construction more than 20 years ago. Tian et al. (2025) state that AI-based strategies have been trending in the management of construction risks over the last decade, such as the identification, assessment, prediction and mitigation of risks, and summarises that AI techniques, such as machine learning, computer vision and natural language processing, were used to identify, predict and analyse risks at different stages of a construction project. Kineber et al. (2024) further note that AI appli-cation in construction can enhance health and safety and speed up construction com-pletion, which suggests that there are high perceived values in these areas.

Hazard detectors or worker-equipment trackers (identified through site images and videos) are typical of safety-oriented applications that use computer vision models and are occasionally assisted by BIM to obtain spatial context (Pan and Zhang, 2021; Regona et al., 2023). Risk ana-lytics can be done with historical incident data, schedule deviations or environmental conditions as a predictor of risk levels. These applications can be connected to PMIS through the safety registers, non-conformance reports, method statements and risk logs, which are now more likely to be housed in the project platforms (or integrated document man-management systems). However, the issues of adoption are still noteworthy. According to Tian et al. (2025), the current AI-based risk tools tend to be developed based on single datasets and rarely linked to project management systems, building information modelling (BIM) or other information systems and that the application of AI-based risk management tools is discouraged by the absence of digitalisation of project information, unstructured historical data, and the reluctance to change the existing risk practices.

Document-Centric AI and Natural Language Processing

Construction projects produce a lot of unstructured and semi-structured data which forms a rich yet complicated source of AI data. As highlighted by Ding et al. (2022), unstructured and semi-structured data (emails, PDFs, images, CAD drawings, IFC models, etc.) are rich in a construction project, which opens the potential of natural language processing (NLP) to aid the knowledge representation, information retrieval, and reasoning processes over project documentation. It can be used in automated verification of specifications and contracts, sorting of work orders and RFI, and access to applicable safety or regulation provisions. As an example, Moon et al. (2022) explain that an automated specification review system is a system that uses natural language processing and rule-based reasoning to detect possible cases of non-compliance and lack of consistency in construction specifications, and that the system can be incorporated into existing document management systems to offer automated feedback to designers and reviewers in the specification development process.

Recent research also investigates retrieval-augmented generation (RAG) and large language models as a way to retrieve knowledge about construction. Lee et al. (2024) mention that it is a time-consuming and error-prone effort to extract the knowledge related to safety in the unstructured texts produced by the construction industry, and indicate that RAG-based safety assistants could be employed to integrate into the construction information systems, and allow project managers and safety engineers to access the required information on regulations, best practices, and accident reports in a timely manner. Similarly, Wu et al. (2025) claim that the system based on RAG may enhance the effectiveness of communication and enable the management of construction processes by solving the issue of the granularity discrepancy between long documents and brief user requests.

Meanwhile, the NLP literature emphasizes that the existing applications remain selective and that the sophisticated generative models are yet to emerge. Ding et al. (2022) note that at the current stage, the technologies and models of NLG are significantly less prominent than those of NLU in the construction industry (only two articles were relevant to NLG). This implies that, although PMIS in construction are increasingly accommodating substantial amounts of documents, their use with AI has not yet been oriented towards content creation but continues to be primarily oriented towards understanding (classification, retrieval, compliance checking) and that adoption of such systems into daily project platforms is relatively low.

Lifecycle-Wide and Integrated Decision Support

A number of reviews seek to generalise AI applications in the construction project life cycle. Abioye et al. (2021) believe that, as more and more data is being generated during the building lifecycle, and other digital technologies come into existence, AI can tap into these data and exploit the abilities of other technologies to enhance construction processes and divides technologies into categories: computer vision, robotics and NLP are emerging technologies; ML, automated planning and scheduling are ripe technologies and KBS and optimisation are mature technologies. This maturity distribution suggests that, as far as readiness is concerned, certain AI techniques (e.g. optimisation, knowledge-based systems) are more mature, others (e.g. computer vision, robotics, advanced NLP) remain under construction. Datta et al. (2024) and Lai et al. (2025) continue to demonstrate that AI applications are centred on design and construction steps with less emphasis on early planning and handover and that most research is centred on technical feasibility and not operational integration.

Notably, various researchers emphasize that one of the sources of bottlenecks is data and system conditions. According to Regona et al. (2022), data fragmentation among disconnected systems is one of the key impediments to analytics and AI applications in construction projects, and that construction organisations tend to have weak digital infrastructures and integrated information systems, hindering their capacity to collect, store, and analyse the data needed to run effective AI applications (Regona et al., 2022). Chen et al. (2025) also note that the majority of AI applications in the construction of infrastructure are designed as single-purpose tools or test projects and do not interface with enterprise information systems and project management platforms, but state that at the same time, AI-based models in infrastructure construction are also dependent on high-quality historical information to train and validate. Datta et al. (2024) underline that application of AI and ML in actual projects is still underdeveloped because of the issues regarding data availability, data quality, and the absence of standardised digital workflows.

These are the problems that are closely related to PMIS architectures in construction. The primary settings where schedule, cost, risk, quality, safety and document information is stored and shared include project web platforms, BIM-integrated systems and

other PMIS. Jahanger et al. (2021) demonstrate that digitalisation of construction-phase information management enhances transparency and allows more reliable decision-making, however, also indicate that to achieve the benefits, it is necessary to ensure uniform data structures, interoperability of information systems, and a clear role in information creation, updating, and approving. Pan and Zhang (2021) note that, although AI is pushing construction towards “constant innovations towards digitalization and intelligence,” the “adoption of AI techniques still lags behind the process in other industries” despite the “considerable amount of engineering data” that projects generate.
Lastly, organisational and capability constraints influence the practicality of AI applications in reality. Regona et al. (2022) identify the following problems as critical barriers such capability/skills gaps, organisational resistance, data and governance issues, and concerns about costs and uncertain returns. Similar barriers are listed by regona et al. (2022), such as data quality issues, lack of standardisation, change resistance, AI knowledge limited, and unclear return on investment. The results are consistent with the perception that AI/ML preparedness in the construction sector is not just a matter of functionality of the system but resources, expertise and administration.

Implications for PMIS and AI/ML Readiness in Finnish Construction

On the whole, existing AI/ML solutions in construction are applied to most of the same areas that PMIS modules include schedule and cost management, safety and risk monitoring, quality control, and document management, and may use data that, in theory, would be stored in PMIS, BIM systems or closely integrated project platforms. Nonetheless, a lot of it is still task-oriented, prototypical and loosely related to the integrated project information systems that practitioners work with daily (Datta et al., 2024; Chen et al., 2025; Regona et al., 2022). Meanwhile, the literature suggests that successful AI implementation necessitates standardised and data integrated data structures, strong digital infrastructures, and organisational support of new workflows (Jahanger et al., 2021; Regona et al., 2022).

To this thesis, these trends indicate a key question within the scope of RQ1: since AI/ML applications in construction are increasingly reliant on the data and processes orchestrated through PMIS, to what extent are the PMIS in current use in Finnish construction prepared, in terms of the quality and breadth of data, system integration, process standardisation and organisational capacity, to host and scale such AI/ML capabilities? The following sections (2.3 and 2.4) expand on this introduction by looking at how the concept of AI readiness has been conceptualised both at the organisational and technical levels and how these two dimensions can be mapped into a multi-dimensional conceptualisation of AI/ML readiness of PMIS in construction.

2.4 Organisational readiness and adoption of AI/ML in construction

2.4.1 Generic AI readiness frameworks

Organisations need more than just technical models to go from isolated pilots to sustained use of AI in their PMIS — they need to be prepared at all strategic, organisational, data, and human levels. The aim of this section is to overview general AI readiness frameworks and understand them as building blocks to AI and machine learn-ing readiness of PMIS - creating a conceptual connection to the construction oriented discussions in Sections 2.4.2 and 2.4.3, and ultimately to RQ1 and Objectives 1 and 2.

Some authors conceptualise AI preparedness as digital transformation. To fit the new use cases of AI, Holmström (2022) suggests an AI readiness framework that considers the adoption of AI as a progressive process where organisations need to align digital infrastructures, data resources and capabilities with new AI applications, arguing that AI readiness is embedded in overall digital transformation, which needs coordinated technology, process, and organisational role changes. On the same note, Jöhnk et al. (2021) de-scribe organisational AI readiness as the degree of preparedness of firms to embrace AI solutions in value-creating terms depending on the supply of data and infrastructures, skills, strategy and governance. They reiterate that the adoption of AI is complex and uncertain and that a knowledgeable decision on the preparedness of an organization increases the likelihood of successful AI adoption and is important to successfully utilize the business value of AI (Jöhnk et al., 2021).

As part of the built environment, Felemban et al. (2024) indicate that AI readiness refers to how well an organisation is equipped with the technological, organisational, and human resources necessary to successfully implement and apply AI in its operations. Their model indicates the four areas of capability that are interrelated, namely technology (including infrastructure), data, organisation and people. They emphasise that readiness factors associated with technology encompass the accessibility of high-quality data, scalable computing infrastructure, and interoperable information systems (Felemban et al., 2024), whereas organisational culture, leadership commitment and employee skills prove to be as significant. Lemos et al. (2025) also add a resource and competitive-pressure perspective, where SMEs struggle to adopt AI tools due to the lack of technological, financial, and human resources, and competitive pressure and external demands can nonetheless push organisations to AI and digitalisation despite the lack of capabilities (Felemban et al., 2024). Stated differently, organisations might be compelled to AI when their internal preparedness is low, which is an especially pressing issue in the project-oriented industries with a large number of small and medium-sized businesses.

These frameworks, although of varied origins, overlap in a number of overlapping readiness dimensions. Issues of strategic and leadership are connected with the presence of a vision of AI, its alignment with the business objectives, and support of the top management (Jöhnk et al., 2021; Shang et al., 2023).. Digital platforms are located in technology and infrastructure, integration mechanisms and computing capabilities- aspects that in project based organisations superimpose on PMIS and the like. Data quality, standardisation, accessibility and governance are linked to data and information management, which are again closely related to PMIS processes of project information (Felemban et al., 2024). People, skills and training involve AI literacy, experience and work in the field and the capacity to work in technical and management roles. Culture

and change readiness include a readiness to experiment, knowledge sharing and tolerance of failure. Finally, governance, risk and ethics contain policies, accountability, transpar-ency and compliance requirements which are of paramount importance when AI is included in decision-support functions.
Project management practice shows that evidence points to AI being viewed as strategically important by many organisations, but they are unprepared in capabilities. Müller et al. (2024) state in a global survey that 76 per cent of the involved professionals are of the opinion that AI will change the way projects are managed, although 62 per cent of them assess AI-related training in their organisations as low and 65 per cent claim to have no or inadequate knowledge of AI concepts and tools. Lai et al. (2025) conclude the reasons why AI should be adopted in project management by stating that AI can help project management in increasing accuracy of its predictions, increasing the speed of processing information, and making decisions that are more informed by data. Hughes et al. (2025) also claim that AI can automate common project management activities, increase the accuracy of data and provide predictive analytics to assist in making proactive decisions, and state that AI can enable project managers to concentrate on higher-level activities by automating routine administrative tasks. Such contributions however require proper skills, training and organisational support which is not usually the case in the current readiness levels.

The role of organisational and institutional context can also be emphasised by Shang et al. (2023) who conceptualise organisational readiness as the availability of technology, skills and other resources and examine AI adoption in terms of institutional pillars regulative, normative and cultural cognitive.. Their research indicates that regulations, industry norms and shared beliefs may advocate or impede the implementation of AI, based on their interactions with the internal capabilities. A similar requirement of alignment is highlighted by Yang et al. (2025), who claim that the implementation of AI in project settings needs alignment of the technological capabilities, organisational processes, and human factors. In this sense, AI preparedness is not an internal characteristic of the IT

role, but a socio-organisational state that is influenced by external forces and internal designs.
The idea of governance and trust, as well as lifecycle thinking, have also gained significance in the AI preparedness. Voting valid AI frameworks, Yang et al. (2025) observe that most frameworks revolve around the following concepts: reliability, robust-ness, explainability, transparency, privacy, and fairness, and present a working framework, which implements these concepts in six stages, including planning, data collection and preparation, algorithm development, deployment, maintenance and archiving. Such lifecycle governance is especially relevant in case AI capabilities are integrated into PMIS since it implies a systematic approach to data curation, model monitoring, access control and accountability. The same argument is made by Regona et al. (2023), who state that the growing access to information on digital projects opens up opportunities to advanced analytics and AI-driven insights but that the opportunities will need proper data governance and platform strategies.

Together, these generic AI preparedness frameworks mean that AI and machine-learning preparedness of PMIS in construction will be dependent on the congruence of PMIS-related technologies, data resources, organisational processes, skills, culture and governance mecha-nisms. These dimensions provide a conceptual starting point in generating PMIS-specific readiness dimensions, and in making sense of the perceptions of Finnish practitioners regarding the readiness of their PMIS, by mapping the cross-sectoral AI readiness literature to RQ1 and RQ2.

2.4.2 AI and digitalisation adoption in construction organisations

Though generic AI preparedness frameworks are valuable in offering dimensions, the construction industry has unique features that influence the nature of the adoption of AI and digitalisation. It is a very project-based construction work, fragmented value chains and temporary multi-organisational coalitions that make it difficult to coordinate investment in digital infrastructures and skills. As Ding et al. (2022) note, the construction industry is among the least digitalized industries, and Jahanger et al. (2021) note that during the construction phase, construction projects produce tremendous amounts of information, but much of it is still processed manually, in a paper-based or semi-digital way. These conditions set the base that affects the digitalisation of the PMIS and the preparedness of the organisations to use AI/ML applications relying on PMIS data.

AI is commonly brought as a possible answer to the productivity and performance issues of the sector. Abioye et al. (2021) state that the construction sector has a productivity issue and numerous other innumerable problems, which can be addressed with the help of AI. They also state that the research results indicate that computer vision, robotics and NLP are emerging technologies, ML, automated planning and scheduling are ripe technologies and KBS, optimisation are mature technologies and show a continuum of AI maturity across methods applicable to construction. Meanwhile, they also highlight that, even with advances in AI techniques, recent, more powerful AI technologies, including deep learning, have not been adopted very fast. According to Datta et al. (2024), the sector is as they put it a slow gradual digital transformation, with AI and ML methods being actively pursued at various points in the project lifecycle with an aim of improving the project decision-making process and productivity, but they point out that currently, the actual implementation in real projects is minimal.

One common obstacle is a limitation in regard to availability, quality and standardisation of data and workflows. According to Datta et al. (2024), the use of AI and ML in actual projects is still scarce because of issues to do with the availability of data, quality of data, and unstandardised digital processes. They also conclude that their review shows that most AI and ML applications in construction projects are dedicated to single tasks like cost estimation, scheduling, and safety monitoring, and that relatively little research is done to discuss the applications of these technologies in a combined system across the multiple stages of the construction project life cycle. Chen et al. (2025) draw the same conclusions to infrastructure projects, stating that, as of 2025, most AI applications in infrastructure construction are developed as stand-alone applications or experimental prototypes, and their connection with enterprise information systems and project management platforms is uncommon, and that AI-based models in infrastructure construction are highly dependent on quality historical data to train and validate. Regona et al.

(2022) emphasize that the lack of data fragmentation in disconnected systems is to date one of the key impediments to analytics and AI applications in construction projects, and Regona et al. (2023) state that despite the growing use of AI to assist decision-making in construction, the integration of AI with digital platforms and project information systems is not explicitly covered in the literature.

These observations are associated to PMIS readiness. Dispersed information in projects with tools that are not connected to each other, paper records and semi-digital processes, PMIS cannot yield coherent and high-quality datasets to AI/ML models, and cannot easily accommodate built-in AI capabilities. Jahanger et al. (2021) demonstrate that digitalisation of information management of construction phases may enhance transparency and facilitate more informed decision-making but also state that this demands organised data, the definition of responsibilities and effective information management procedures. In its argument that BIM-related systems facilitate more data-rich environments to automation and AI, Pan and Zhang (2021) state that integration is not evenly distributed among construction projects, which is why PMIS and BIM should be considered as components of a wider spectrum of digital infrastructure whose maturity may differ significantly across organisations and projects.

The influence of organisational and human factors also shape the adoption of AI and digitalisation in construction, as Regona et al. (2022) list the significant challenges in adoption, such as cost/ROI issues, the lack of skills and expertise, and organisational resistance and capability gaps. Lemos et al. (2025) also emphasize that SMEs, comprising a significant portion of the construction value chain, are constrained in terms of resources, and that the SMEs are not easily able to take up AI tools without the necessary technological, financial, and human resources. They also mention, relying on Ayedee and Kumar, that the less thorough training of employees in digital tools and AI is one of the obstacles. Synthesising critical success factors related to AI implementation in the construction industry, Wuni (2025) concludes that successful projects are more likely to be characterised by capabilities of their workforce, technological infrastructure, strong data and information governance, supportive organisational strategy and culture, and favourable external conditions. Their assessment cautions that without action on workforce training, change, and subpar data governance, the anticipated gains can be jeopardized.

Knowledge management, learning and decision making practices are also put in the limelight of the studies. Khan et al. (2024) demonstrate that knowledge management processes have a strong moderating effect on the relationship between AI capabilities and the performance of the firm in construction SMEs, and emphasize the importance of mechanisms to capture, store and reuse project knowledge to enable AI systems to learn on an existing knowledge base. Al Omari et al. (2023) discuss the impediments to digitalisation in the construction sector and argue that the support of the top management, the clarity of digital strategies and focused training are some of the most important determinants of getting past the resistance and out of the single pilots. Kineber et al. (2024) also discover constructs related to technology, advancement and knowledge to be a substantial factor in the success of AI implementation, which once again emphasizes the interaction between technological and human resources.

Another pair of barriers is trust and perceived risk. Yang et al. (2025) write about the use of AI on site and claim that the lack of trust in the use of AI in construction sites is complicated by the fear of technical maturity, safety and privacy, preventing the rapid process of intelligent transformation and experimentation. According to Tian et al. (2025), in the scenario of AI-risk analysis, stakeholders are concerned with the issue of model transparency and interpretability, which may restrict their readiness to trust AI-generated outputs. A review of AI in construction management by Lai et al. (2025) reports that AI technologies have predominantly been applied to schedule, cost, quality and health-and-safety management, but that other fields of knowledge, like stakeholder engagement or procurement, receive little attention and that current reviews are often focused on specific technologies or management areas and this results in a lack of understanding of the overall role of AI in management of construction. Salimimoghadam et al. (2025) also deploy the same clusters of AI opportunities, enablers and barriers in construction, and also highlight the importance of organisational and cultural factors, with the same weight as technical factors.

These sector specific drivers and barriers, in PMIS terms, become tangible preparedness factors. The absence of standardised workflows (Datta et al., 2024), data fragmentation across disparate systems (Regona et al., 2022), and uneven BIM-PMIS integration (Pan and Zhang, 2021) imply that most construction organisations are yet to have PMIS environments that can support powerful AI/ML models. The implementation costs are high, the skills are insufficient, and the organisational support is weak (Regona et al., 2022; Lemos et al., 2025) which minimise the likelihood of the AI-enhanced PMIS functionalities being adopted or used effectively, even in the case when they are technically available. Meanwhile, competitive forces, customer needs and regulatory demands drive companies toward increasingly data-intensive practices (Lemos et al., 2025; Shang et al. (2023)) and the necessity to appreciate how prepared their PMIS setups are..

The international findings are very relevant to Finnish construction. A number of organisations in Finland have invested in digital platforms and in BIM, and have a policy environment that encourages digitalisation and data-driven decisions. Nevertheless, the literature in the world has indicated that challenges in data quality, system integration, skills, trust and resource constraints are rampant in the construction industry. These trends inspire the core question of this thesis: The core question is how prepared PMIS in Finnish construction are, technically, organizationally, and socio-technically, to support and scale AI/ML capabilities, to accommodate and scale AI/ML capabilities? To answer this question under RQ1 and Objectives 1-2, it is necessary to integrate the generic AI readiness dimensions explored in Section 2.4.1 with the construction-specific patterns of adoption that are examined herein.

2.4.3 PMIS as socio-technical systems

In 2.1 and 2.2, PMIS was defined as multi-purpose digital systems that facilitate planning, control, risk management, document handling and communication in project-based organisations and emphasised its key position in digitalisation and AI/ML applications. The key to grasping AI and machine-learning preparedness of PMIS in constructions is to consider such systems as socio-technical systems where technologies, data structures, organisational structures and human practices are closely linked.

Existing empirical research on the use of PMIS is already indicative towards this direction. Monteiro et al. (2025) demonstrate that the use of PMISs has a significant and positive impact on the performance of project managers, which supports the extent of the importance of these systems as tools that facilitate the project management processes and the decision-making process, and that the presence of both a PMO and PMIS is linked to more professionalised project management structures. Rebuglio et al. (2025) conclude that, in general, PMIS enhances the efficiency and digitalization of project-driven businesses and improves planning, scheduling, collaboration, and proper allocation of tasks, but their role and scope remains unclear. Niederman (2021) places these observations in the context of a wider understanding of information systems by suggesting that AI and digital tools should be viewed through the lens of a modern socio-technical approach in which the relations between social and technical systems create a nexus of interest and that AI capabilities are becoming an integrated part of packaged software instead of being deployed as discrete artefacts. In the case of construction projects, Zabin et al. (2022) define BIM as a collection of interacting policies, processes and technologies that create a methodology to handle the necessary building design and project information in the digital form over the life cycle of the building, implying that BIM and PMIS are socio-technical infrastructures, but not software products.

The fact that PMIS is considered socio-technical systems is even greater with the introduction of AI features. According to Almeida et al. (25), knowledge-based per-spective is that AI tools can be seen as the continuation of PMIS that will transform the information available in the form of stocks into the actionable information, and the performance of such tools depends on the organisational culture, leadership and willingness to share and reuse knowledge. Using Adaptive Structuration Theory, Felicetti et al. (2024) analyse how project managers embrace the use of generative AI tools and find that attitudes towards innovation, peer pressure and task technology fit are critical factors in adopting and integrating this technology into daily work. Their results show that although AI capabilities are technically available, local practices and social interpretations will determine the utilisation of AI capabilities as intended, re-purposed or resisted.

The institutional and governance views further support socio-technical nature of PMIS and AI preparedness. As stated above, Shang et al. (2023) emphasise that organisational readiness is not just a sign of internal re-resources and skills but also regulative, normative and cultural-cognitive pressures; organisations respond to regulations, industry norms, and shared beliefs when deciding how far they should go with AI and digitalisation.. Jöhnk et al. (2021) and Felemban et al. (2024) also highlight that AI preparedness is not just IT infrastructure but also includes strategy, processes, culture and governance. Yang et al. (2025) append that credible AI needs lifecycle governance, which involves planning, data gathering, development, deployment, maintenance and archiving that should be made part of organisational practices. Regarding the PMIS in the construction industry, this implies that the AI capabilities cannot be seen as the technical add-ons; they necessitate changes in the responsibilities and workflows and oversight mechanisms.

There are four components of PMIS in this thesis which are at least interrelated and include: technology (platforms, modules, connectivity with BIM, ERP, and site tools), information structures (data models, templates, workflows, and metadata), people (project managers, planners, site staff, clients and other stakeholders), and organisational arrangements (roles, rules, routines and governance mechanisms). It is also among socio-technical perspectives of RQ2, which will be addressed based on the question how project managers and planners in the Finnish construction describe the current preparedness and the key development requirements of their PMIS to AI and machine learning. Most likely, their perceptions will not be based only on the technical capacities of systems, but on the organisational support, training, data practices, responsibilities and trust towards the digital tools. The thesis will be in a position to apply the socio-technical approach to interview data to relate the tales of practitioners to the dimensions of readiness that were presented in 2.3.1 and 2.3.2.

Lastly, such a view preconditions the following parts of the literature review. In section 2.4 and 2.5, the socio-technical understanding of PMIS will be leveraged to develop more concrete dimensions of AI/ML preparedness in terms of data and the technical infrastructure on the one hand, and governance, trust and ethical considerations on the other. It is also essential to conceptualize PMIS as socio-technical systems to assess their AI and ma-chine-learning readiness in Finnish construction and to align the generic AI readiness paradigms to the specifics of the applied PMIS..

2.5 Data and technical readiness for AI/ML-enabled PMIS

Sections 2.1–2.4 demonstrated that PMIS are at the heart of the digitalization process of construction projects, but organizational readiness; data quality and socio-technical factors influence the potential of AI/ML technology. The focus here is on the technical and data aspects of this readiness. Structured project data (e.g., BIM/IFC models, scheduling and cost reporting) and unstructured or semi-structured information (e.g., specifications, contract documents, RFI and safety reports) are identified and the implications for PMIS architecture in construction are outlined with a view to assessing PMIS AI and machine learning readiness under RQ1.

2.5.1 BIM and structured project data as enablers for AI

In the PMIS perspective, the availability of high-quality and structured data is an evident beginning of AI and machine-learning preparedness. According to Zabala-Vargas et al. (2023), organizations are currently faced with the high amount of information generated by project management and its quality, and that the new technology of big data, data science and AI are thus being considered as an alternative to manage this information throughout the project life cycle. A lot of this structured information in construction flows through or beside PMIS schedules, cost and progress records, risk registers, resource plans and other performance indicators. When such streams of data are disaggregated or irregular, AI models cannot be trusted to learn patterns, and PMIS are still constrained to simple reporting, not predictive or optimisation.

One of the most significant sources of AI in construction data are Building Information Modelling. According to Zabin et al. (2022), as the BIM workflows gain relevance throughout the project life cycle, more data is generated and processed throughout the life cycle, and the information stored in the BIM-based projects offers a chance to analyse and extract the project knowledge between the inception and the operation phase. Nevertheless, they also note that even today, most practitioners view BIM in the light of a single application, which is to use software to create 3D models, when the latter, according to Sacks et al., refers to BIM as a set of interacting policies, processes and technologies that must manage the fundamental building design and project data in a digital form throughout the lifecycle of the building (Zabin et al., 2022). This more general perspective is essential in AI/ML perspective: BIM is not merely a renderer but also a database of objects, attributes, relationships and time-related data that could potentially be used to perform high-level analytics. This mountain of information as defined by Zabin et al. (2022) can be regarded as a centralized machine-interpretable mine, as it follows a structured schema.

Pan and Zhang (2021) also point to the fact that construction engineering and management is undergoing a rapid digital transformation that is being driven by AI, and that there are six hot research topics that enhance the benefits of AI in CEM, such as knowledge representation, information fusion and process mining. The techniques are especially appropriate in BIM-integrated environments as they offer uniform digitalisations of assets, activities and constraints. Rane (2023) elaborates on this reasoning by stating that BIM is an information centre, uniting geometric, semantic, and temporal information throughout the project lifecycle, and that AI can be employed to analyse such information to optimize the scheduling, resource allocation, cost estimation, and risk prediction. Combined, these studies indicate that AI/ML-capable PMIS in the construction sector will be forced to become more and more interoperating with, or integrating into, BIM-based data formats to facilitate more advanced planning and control capabilities.

One of the major enablers in this regard is standardisation via Industry Foundation Classes (IFC). According to Du et al. (2024), IFC is defined as a file format that is supposed to be the hub data of construction projects, and thus, using IFC files as a dataset to train AI is a logical next step. Concurrently, they caution that the approaches to successfully converting data of BIM formats, including Industry Foundation Classes (IFC), into the format compatible with AI applications are yet to be examined and summarize that the current state of BIM-AI data preparation is in the middle stage. Their survey indicates that three key technical barriers include: lack of time-series data properties, heterogeneous geometry information, and the necessity of a toolchain to extract data in full (Du et al., 2024). Practically, this implies that even on the occasions that both BIM and IFC are available, they remain difficult to connect in a systematic manner with schedule histories, cost development and risk events in a manner that AI models can utilize.

These are not just academic problems, but they come into practice in project information systems. The authors note that construction projects produce volumes of information at the construction stage, which are still processed to a large part through fragmented and semi-digital practices (Jahanger et al., 2021). They demonstrate that the information management of construction phase can be enhanced through digitalisation, which can enhance transparency and offers a more reliable source of information to make a decision or resolve a dispute, yet emphasises that it necessitates the consistency of data structures, integration of information systems, and clear responsibilities to create, update, and approve information (Jahanger et al., 2021). Regona et al. (2022) also indicate that construction organisations do not always have a strong digital infrastructures and integrated information systems, which restricts access to data required to use AI effectively. These results, in terms of PMIS, suggest that organized data preparedness to AI hinges not merely on BIM adoption as such, but also the extent to which BIM, schedules, costs and other project data are incorporated within coherent PMIS or platform structures, instead of existing independently.

This requirement is supported by the PMIS literature. Van Besouw and Bond-Barnard (2021) observe that project data are usually disjointed and embedded across various systems, and suggest a Smart PMIS architecture that is supposed to enable the integration of software and smartness according to identified industry needs and requirements. The same description is made by Ruguglio et al. (2025) who state that PMIS assist in the optimisation of resource allocation, ease monitoring and control, and risk management, and suggest that PMIS enhance the efficiency and digitalisation of project-driven companies. When BIM and IFC data can be considered a subset of this PMIS landscape, whether by integrating BIM viewers and data links into project platforms or by integrating PMIS and typical data environments, the centralized machine-interpretable mine of Zabin et al. (2022) will be available to AI/ML-enabled decision support.

In the case of this thesis, the implication is that the AI and machine-learning preparedness of Finnish construction PMIS will be heavily contingent on the effectiveness of the capture of BIM and other structured project data, its standardisation and availability via integrated system architectures. In any case where BIM/IFC is always modelled and connected to schedules, costs and risk registers, PMIS can offer a firm base under which the AI-based forecasting, optimisation and risk analysis can occur. The inconsistent nature of modelling practices and the loose linkage of PMIS with BIM and other sources of data imply that a structured readiness of data to AI/ML is still incomplete, as it directly impacts the evaluation of the existing PMIS under RQ1 and Objectives 1-2.

2.5.2 Unstructured information: NLP, RAG and document-centric AI in construction

Although BIM and structured records are of significance, much project information in construction is kept in the form of unstructured or semi-structured text. Ding et al. (2022) emphasize that, during the process of digitalisation, data in construction-related areas are represented in one of the multiple types of electronic text, Word, Sheet, Email, Extensible Markup Language (XML), Hypertext Markup Language (HTML), Portable Document Format (PDF), Computer-aided Design (CAD), Industry Foundation Classes (IFC), etc., all of which include human They point out that, being a fundamental subdivision of

AI, NLP offers a smart method to process such types of text data, allowing the intelligent agent to learn natural language and automatically finish knowledge representation, retrieval and reasoning process in a human-like manner, and conclude that NLP technologies have been the key to helping reach further intelligence in construction-related spheres (Ding et al., 2022). Simultaneously, they caution that one of the critical issues that have to be addressed is the data isolation that leads to the inability to reproduce research and that isolated applications of NLP alone cannot satisfy the requirements of the industry in the future (Ding et al., 2022). In the case of AI/ML-readiness of PMIS, it implies that document and communication repositories have to be treated as first-class data sources instead of archives.

Document-centric AI in construction has concrete examples in specifications and documentation of construction maintenance. According to Moon et al. (2022), construction specifications are lengthy and complex documents and manual reviews are time-consuming and subject to human error. They create an automated specification review system which uses natural language processing and rule-based reasoning to find potential non-compliance and inconsistency problems in construction specifications (Moon et al., 2022). They find that a system like this can greatly decrease the time on specification checking without compromising detection performance with human experts. Though the implementation is introduced as an automated reviewer, it is conceptually analogous to a PMIS feature: it is run on project documents, identifies problems and gives structure feedback to designers and reviewers.

The article by Li et al. (2024) discusses maintenance work orders (MWOs) and notes that MWOs recorded are the so-called good potential data source to aid the maintenance activities, however, the unstructured nature of textual data is the reason behind the difficulties in utilizing work order information (Li et al., 2024). Their NLP-based system is an automatic work order generator and NLP-based work order analyser, which helps to enhance the maintenance management practices. Systems-wise, the current computerised maintenance management system they had effectively was nothing more than information storage, and the allocation was done manually and at times randomly based on the scheduling (Li et al., 2024). This comparison of a passive information warehouse and an AI-enhanced system that organizes the text and helps to make allocation decisions demonstrates precisely what the difference between a typical document warehouse in a PMIS and an AI/ML-enhanced PMIS module is.

The recent advancements of large language models and retrieval-augmented generation (RAG) further enhance the opportunities to use unstructured project information. Lee et al. (2024) note that the construction industry produces a significant amount of safety-related documents, and that the process of finding the necessary knowledge in such unstructured texts is a time-consuming and inaccurate activity. They contrast RAG and fine-tuned large language models on the safety management knowledge retrieval by prioritizing the accuracy, response time, and the ability to handle noisy queries (Lee et al., 2024). They find that the RAG-based model is more precise and generalises better to unseen safety queries than the fine-tuned LLM, which emphasizes the value of a trustworthy domain-specific retrieval (Lee et al., 2024). Practically, RAG is a search method that finds the passages in a corpus of project files that contains the relevant passages, alongside a language model which generates answers based on those passages. Instead of substituting project information systems, it relies on them as organized points of safety manuals, procedures and incident reports.

Wu et al. (2025) look at information retrieval and question answering in construction management in general. They note that although digital tools, including ERP and BIM, have been implemented, information retrieval in CM still poses a big engineering problem as project documents are lengthy and queries might only cover minor sections of the documents (Wu et al., 2025). One of the causes is the incompatibility of the granularity of queries and CM documents: construction management documents are long (e.g., hundreds of pages), and a query is often related to a small part of the documents (e.g., a few sentences) (Wu et al., 2025). Their prototype, RAG-driven (RAG4CM), is meant to deliver multi-source information retrieval in a friendly way, therefore enhancing the efficiency of communication and facilitating the construction management processes. Once again, it is based on the assumption that the relevant documents are in a digital form and are indexable. The AI layer solves the retrieval, matching and summarisation issues that exist in the current platforms.

These studies imply a number of implications on PMIS data and technical preparedness in the unstructured side. To begin with, because PMIS and similar project platforms can serve as primary document and communication hubs, their design defines the extent to which NLP and RAG-type services can be easily implemented. In case files are dispersed to email inboxes, local drive and various unrelated systems, which would raise the issue of isolation of data as raised by Ding et al. (2022), AI services cannot access the entire corpus. Second, AI-ready PMIS will require the ability to store the main categories of documents (contracts, specifications, RFIs, site diaries and safety reports) and metadata, version histories and access controls that can be safely indexed. Third, it requires technical interfaces, like APIs or connectors, to enable outside NLP/RAG engines to query PMIS repositories and feed their results back into the user interface, as Moon et al. (2022) envision when they propose to add automated specification review to existing document platforms.

Ding et al. (2022) also note the fact that although state-of-the-art models of NLG, like BERT and GPT, are becoming more popular, the rate of appearance of NLG in the construction domain is much lower than NLU. It means that most of the short-term AI/ML-enabled PMIS uses in construction will remain limited to the understanding and organization of existing text (search, classification, extraction, compliance checking) and not fully automated construction of project documents. In the case of Finnish construction, where project platforms already support large amounts of digital documents, the answer to the question under RQ1 is hence not whether there is unstructured data, but whether PMIS configurations and data practices are technically equipped to allow integration of such NLP and RAG services.

2.5.3 Technical implications for PMIS data and system architectures

Combining formal and informal data views, AI/ML-based PMIS in the construction sector must be able to work in two overlapping worlds of data. Structured datasets, such as BIM/IFC objects, schedules, cost and progress records, risk registers and other coded information, can be found on one side. In the other side are unstructured artefacts, or semi-structured artefacts like specifications, contracts, RFIs, safety reports, email chains.

Zabala-Vargas et al. (2023) highlight that big data solutions in the AEC should consider analyzing both structured and unstructured data, including historical reports, sensor reports, real-time data, and customer feedback, to detect patterns and offer a holistic view of project performance and status. In the case of PMIS, AI and machine-learning readiness thus imply the capability to unify, process and reveal both forms of data in a manner that can be capitalized upon by AI tools.

On the structured side, the requirements of technical readiness are based on the BIM and data readiness literature. Du et al. (2024) emphasize the fact that IFC is a natural choice of central data repository of AI, but data extraction is challenging, especially because of the lack of time-series properties, heterogeneous geometry, and the lack of robust extraction toolchains. Zabin et al. (2022) demonstrate that IFC is often cited as the main schema in the ML-to-BIM applications, but the entire field is in its infancy, and much remains to be done to adopt it effectively. A more applied example is given by Al-Sinan et al. (2024): their ML-BIM model of construction schedule generation uses past project schedules and BIM models to train machine-learning models to make predictions on the length of activities and their sequencing rules, but note that the research is limited by the availability and quality of BIM data, standardisation of activity definitions, and integration of ML tools with existing project management information systems. These findings align with those of Regona et al. (2022), who observe that construction organisations frequently do not have strong digital infrastructures and integrated information systems, restricting their data collection and analysis to AI.

In the case of unstructured information, the demands are based on document repositories, indexing and interfaces. Lee et al. (2024) show that RAG-based safety assistants are more accurate and generalise better than the fine-tuned LLM, when they have access to domain-specific safety document corpora. Wu et al. (2025) demonstrate that despite the availability of ERP and BIM platforms, retrieval of information is challenging because of the granularity differences between long documents and small queries, and suggest RAG4CM to enable multi-source retrieval in an effortless manner. Moon et al. (2022) specifically remark that their automated specification review system may be incorporated into the existing document management systems to offer automatic feedback to the designers and reviewers in the process of specification development. Li et al. (2024) emphasize that in their case, the current maintenance management system operated as a mere warehouse whereby work order assignment was conducted in an informal and manual way. Collectively, these findings suggest that AI/ML-prepared PMIS should go beyond mere repositories to systems that enable advanced indexing, document search and automated reasoning, supported by an appropriately designed APIs and service interfaces.

This architecturally is towards more integrated and modular designs of PMIS. Van Besouw and Bond-Barnard (2021) believe that project data is commonly scattered and hidden in various systems, and introduce a Smart PMIS model that brings together various sources of data and allows the integration of software and intelligence to track performance and reporting. The same authors, Regona et al. (2023) also discover that, despite the growing use of AI to aid decision-making in the construction industry, the integration with digital platforms and project information systems is often not explicitly discussed in the literature, and propose that research should be conducted on how AI methods can be integrated into construction information management systems to facilitate more sustainable and data-driven delivery. Tian et al. (2025) state that the existing AI cantered tools are usually trained on disconnected datasets and seldom coupled with project management platforms, building information modelling (BIM), or other information systems and suggest that platform-based solutions, wherein AI techniques are deployed as part of digital construction ecosystems and not isolated tools. Chen et al. (2025) also note that AI applications in infrastructure construction are often stand-alone prototypes, and are still uncommon in enterprise systems and project management platforms.

The implications of these findings can be directly applied to PMIS architecture evaluation with regards to AI/ML preparedness in Finnish construction. To start with, the concept of integration and interoperability becomes a key technical preparedness variable: PMIS has to be capable of sharing data with BIM/CDE environments, ERP and site tools, in standardised formats where possible, like IFC. Second, consolidation and quality control of the data should be required: PMIS is to facilitate the use of the same data models more schedules, costs, risks and other main project entities, and mechanisms to connect these to BIM objects and documents. Third, document management features should be adequately advanced to enable indexing and search by NLP and RAG services, considering metadata, access and versioning. Fourth, PMIS should have modular architectures with open APIs or plug-in systems that can accommodate AI services to forecast, optimise, classify or question answer without having to fully replace the system.

Putting these together, there are at least five data and technical preparedness factors to AI/ML-enabled PMIS in construction synthesised:

1.Project data standards and quality - uniform application of schemas like IFC, standardised activity and cost structure, and trusted time-series schedule and progress records (Du et al., 2024; Zabin et al., 2022; Al-Sinan et al., 2024).
2.BIM integration with PMIS- practical mechanisms, connecting the BIM/CDE environments with PMIS modules of schedule, cost, risk and change management, instead of BIM being viewed as a distinct design tool (Rane, 2023; Jahanger et al., 2021).
3.Integrated document repositories- centralised, well-organised storage of specifications, contracts, RFIs, safety reports and others in digital platforms that are linked to PMIS without the isolation of data that is promoted by Ding et al. (2022) and Regona et al. (2022).
4.AI service APIs and connectors - technical interfaces that enable NLP, RAG and ML service to query PMIS data and documents and provide structured responses to users (Lee et al., 2024; Wu et al., 2025; Moon et al., 2022).
5. Data governance and responsibility measures - the existence of data creation, updating and approval responsibilities, and data use and quality control policies, which Jahanger et al. (2021) refer to as the prerequisites of the benefits of digitalisation, and on which the AI/analytics implemented on the top is based.

These factors will be employed in this thesis in the conceptual background of AI and machine-learning preparedness of PMIS (Section 2.7) and will be used to interpret the interview data on Finnish construction practice under RQ1 and RQ2. They transform the overall concept of data and technical readiness into more specific criteria with the help of which the current PMIS set-ups and developmental requirements can be evaluated.

2.6 Governance, trust and change management for AI/ML-enabled PMIS

2.6.1 Trust, transparency and human–AI collaboration

Although data and technical conditions may be there (Section 2.4), the AI/ML-enabled PMIS will not be put into practice unless the project stakeholders trust its outputs and perceive that they can still have a significant influence on the decisions. Tian et al. (2025) state that in construction risk management, stakeholders voice their concerns on how AI-generated risk assessments are transparent and interpretable, thus constraining their readiness to use such tools in making important decisions. Where predictions have safety implications, cost contingencies or schedule buffers, opaque models incorporated in PMIS can easily be sidelined irrespective of their statistical performance.

Trust problems are supported by the greater questions of reliability, safety and privacy. According to Yang et al. (2025), concerns over technical maturity and privacy concerns have been the cause of distrust to AI among stakeholders and end users in the construction industry, which hinders implementation. Examining the current frameworks and guidelines, they note that the majority focuses on such principles as reliability, safety, explainability, transparency, privacy, and fairness as the preconditions of the trust of the population (Yang et al., 2025). In particular, explainability can be defined as the capability of relevant parties to access, interpret, and understand decision-making processes (Yang et al., 2025).

). In the case of AI-enhanced PMIS, it means that forecasts, risk scores or flags of anomaly must be supported by explanations that are easy to understand, summaries of the input or reference cases, but not as unintelligible scores.

By 2030, Hughes et al. (2025) on the one hand, state that predictive insights and modelling capabilities will be driven by AI and will, according to the authors, improve efficiency significantly, on the other hand, these developments will also bring critical questions concerning the future role of human project managers. Predictive modules in the PMIS context can enable the work of project managers to be less about manual monitoring and more about interpretations and disagreements with algorithmic suggestions. The positive or negative perception of this change by Finnish project managers will be determined by how transparent the systems are in displaying assumptions, the level of confidence and data sources, and interfaces of PMIS can be used in dialogic rather than in one-way automation.

Yang et al. (2025) also clarify that good models are not enough to create trustworthy AI, but lifecycle-oriented governance. Their six-phase model planning, data collection, algorithm development, deployment, maintenance and archiving emphasizes that decisions regarding data selection, labelling, monitoring and retirement can all impact trust. In the case of AI/ML-ready PMIS in Finnish construction, this implies that trust, transparency and successful human-AI interaction should be built into the entire lifecycle of PMIS-integrated models and manifested in the way project managers and planners feel about risk dashboards, forecasts and recommendations under RQ1 and RQ2.

2.6.2 Governance, ethics and risk management for AI in project information systems

Governance question is also the AI/ML preparedness of PMIS: who determines the rules according to which data, models and recommendations are developed, tracked and utilized? Tian et al. (2025) note that although the model-level results are promising, the application of AI to risk management practice in the real world is underused, and most studies do not consider the organisational processes and the governance mechanisms required to implement it. And, in the absence of well-defined model validation procedures, the AI-assisted risk registries or risk early alerts in PMIS are unlikely to be trusted in contract management or procurement choices.

This layer of governance includes ethical considerations that are the core of this layer. Hughes et al. (2025) insist that AI must be guided by ethics in its policy making and decision making processes, and that ethics of AI will become a pillar of the profession, to guide the impact of AI towards equitable, transparent and accountable results. Within the framework of a PMIS, it casts doubt on training data bias (such as underestimating risk of some types of projects), the equity of resource-allocation recommendations, and the responsibility of decisions when AI-informed recommendations are implemented or not.

Yang et al. (2025) urge towards a responsible and reliable AI framework that regulates implementation in the lifecycle of the system, which is organized into six phases, comprising planning to archiving. Such lifecycle governance applied to PMIS would include, e.g., curation of project data to train on, management of access control and logging when models access PMIS databases, performance drifts, and model retraining or retirement. It also involves the way risk forecasts or schedule advice generated within PMIS is recorded in project documentation, to enable accountability in the event that decisions are disputed in the future.

At the organisational level, Wuni (2025) list the following critical success factors of AI implementation in construction projects: a clear AI strategy, well-supported top management, and sufficiently available and quality data and technology infrastructure. The same themes can be found in more general AI preparedness literature where strategy, governance structures and investment plans are frequently absent yet the interest in AI is present (e.g. Jöhnk et al., 2021; Felemban et al., 2024). In the case of Finnish construction, this implies that the preparedness of PMIS in regards to AI/ML will not only be determined by the technical possibility of project platforms, but equally by whether organisations have established who owns and validates PMIS data used by AI, how AI-based recommendations can be disregarded and who is responsible when AI-based decisions cause delays or cost increases. Within the context of RQ1, such governance arrangements constitute a separate dimension of readiness; within the context of RQ2, it is likely that such governance arrangements might be reflected in the way project managers articulate trust, responsibility and perceived risks in the context of AI-enhanced PMIS.

2.6.3 Change management and capability building for AI-ready PMIS

Last but not least, AI/ML-enabled PMIS will not be able to provide value unless change management and capability building are planned. According to Hughes et al. (2025), project managers will have to become AI literate in order to make their way through this high-tech landscape, though once again, ethics of AI will become a key part of the profession. It means that the users of PMIS in Finnish construction are expected to have a minimum of a general idea of what AI modules in their systems can and can not do, as well as how to challenge the outputs and whether they are aware of ethical and data-protection concerns.

Multiple studies emphasise that skills and organisational capabilities tend to be the weakest link. According to Müller et al. (2024), 62 percent of the surveyed professionals rated their companies at 4 or lower (out of 10) regarding the provision of AI training, and 65 percent have no or basic AI knowledge. The same authors (Lemos et al., 2025) observe that the biggest obstacle to AI adoption in small companies is the lack of employee training. Regona et al. (2022) and Shang et al. (2023), in turn, consider the absence of skilled, trained employees as a key obstacle in construction, whereas Regona et al. (2022) underline that the training of the workforce is required in addition to technical investments.. The results indicate that AI/ML preparedness of PMIS needs to clearly state training, support and learning frameworks of project managers, planners and PMO employees.

In a construction-specific standpoint, Rane (2023) believes that to ensure successful BIM AI solutions, it needs effective data governance, the definition of roles in data creation and maintenance, and training programmes that develop AI awareness and skills. This is also in line with the focus of Jahanger et al. (2021) on clear accountabilities in information creation, updating and approval in the digitalised information management. Khan et al. (2024) include knowledge-management lens, suggesting that managers should build knowledge management capabilities and cross-functional knowledge integration in such a way that AI adoption does make a difference and aligns with organisational strategy. In the case of PMIS, this does not just imply the training of users to work with new features, but also the creation of routines which can be used to learn about the lessons learned by early AI-enabled pilots and to share experience across projects and to update data standards and workflows in response to this experience.

The appropriation of AI capabilities as part of PMIS is also affected by human attitudes and social influence. Felicetti et al. (2024) show that “Innovation Attitude and Peer Influence” positively affect the creative and sometimes “unfaithful” use of generative AI tools by project managers, and that Task–Technology Fit is crucial for effective integration. Likewise, Wuni (2025) classifies critical success factors in groups based on the workforce capabilities, organisational culture and technical infrastructure with a warning that AI benefits can be spoiled by inability to deal with training, change resistance, and poor data governance. To Finnish construction organisations, this is an indication of the need of change programmes that involve technical PMIS development and user engagement, top-management sponsorship and supportive roles within PMOs that orchestrate training, standardisation and experimentation.

Combined, Sections 2.5.1–2.5.3 indicates that governance, trust and capability building are key socio-organisational pillars of AI/ML preparedness to PMIS in construction, alongside the data and technical aspects covered in Section 2.4. These pillars influence the way in which Finnish project managers and planners are bound to see the readiness, as well as the development requirements of their PMIS (RQ2), and they will be referred to, alongside the technical and organisational aspects worked out in Sections 2.3 and 2.4, in Section 2.6 when discussing project and PMIS success in the context of AI and ML, and in Section 2.7 when.

2.7 Project and PMIS success in the context of AI and machine learning

2.7.1 Project and PMIS success concepts

Various definitions have been used to describe project success in construction, the most common definition being the ability to deliver the agreed scope within acceptable time, cost and quality, and client expectations, safety requirements and more and more sustainability and regulatory requirements. The cost and schedule performance are especially in the center of attention as delays and overruns are a common occurrence in construction projects (e.g., Datta et al., 2024). As viewed through the prism of a project owner, the digitalisation of construction-phase information management is likely to enhance the transparency and control over such outcomes, as well as give more credible records to make decisions and resolve disputes (Jahanger et al., 2021).

The PMIS success is typically measured in terms of the extent to which the system facilitates these goals through the provision of timely, accurate and usable information to aid in planning, monitoring and control. Empirical research about PMIS and construction digitalisation indicates that properly implemented systems can enhance the planning and scheduling, facilitate collaboration and delegation of tasks, and improve transparency and record-keeping to project owners (Jahanger et al., 2021; van Besouw and Bond-Barnard, 2021; Regona et al., 2022).

Success of PMIS thus possesses both system and outcome oriented aspects of success: system and information quality, actual usage and user satisfaction, and, most importantly, impact on project performance. In construction, it involves facilitating the coordination of numerous actors, the combination of data based on BIM, site tools and financial systems, and the creation of dependable schedule, cost, risk and quality monitoring (van Besouw and Bond-Barnard, 2021; Regona et al., 2022). Within the framework of this thesis, project, and PMIS success serve as the point of reference that AI/ML-ready PMIS must eventually be measured by: it is only meaningful when it facilitates the project organisations in the Finnish construction industry to reach these types of success (RQ1, RQ2).

2.7.2 Evidence on AI/ML impacts on project or project-management performance

An increasing amount of literature indicates that AI and machine learning can facili-tate the enhancement of key project management aspects. The systematic reviews of AI in construction and project management have shown that AI approaches have been used to enhance precision of forecasting schedule and cost, risk evaluation, and safe-ty and quality control (Abioye et al., 2021; Datta et al., 2024; Adamantiadou and Tsironis, 2025; Regona et al., 2022). Zabala-Vargas et al. (2023) note that AI has the ability to handle substantial amounts of project data, find patterns and forecast pro-ject performance, assisting project managers to modify planning and resource place-ment in real-time.

The expectations are strengthened by survey-based studies. In Fridgeirsson et al. (2023) survey, about 50 percent of the respondents expect a tremendous or high influence of AI on the schedule, cost and risk management, particularly in scenarios where past data can be utilised to plan and estimate. Müller et al. (2024) find out that three-fourths of professionals believe that AI will alter project management, and conclude that data collection and reporting, performance monitoring, and time management and scheduling are the most important areas of influence. These spheres are directly mapped onto common PMIS modules, so in theory, AI-enhanced PMIS might be significant in terms of achieving these expected benefits.

There are studies that are specific to construction which give more detailed illustra-tions of the effects of performance, but in limited settings. Al-Sinan et al. (2024) demonstrate that a machine-learning-based approach with BIM and past schedules can produce viable construction schedules similar to those obtained by professional planners and greatly decrease efforts in schedule production. Moon et al. (2022) es-tablish that automated specification review can save time required to check compli-ance and achieve an equal level of detection performance with human experts and Li et al. (2024) discover that automated maintenance work order assignment using NLP can be highly accurate with a high F1 score. Similarly, RAG-based/automat-ed assistants can make the process of being informed about safety and project documentation faster (Lee et al., 2024; Wu et al., 2025).

Tian et al. (2025) observe that AI-based methods have been extensively discussed in the context of risk identification, risk evaluation, risk prediction, and risk mitigation where the model-level results are promising. Nonetheless, they also observe that such applications are still restricted in practice and that tools are frequently created on a separate datasets, which are rarely connected to project management applications or BIM (Tian et al., 2025). Surveys of AI applied to BIM data indicate that the application is in a growing area of research, but that the general use of BIM data by machine learning is at an early phase (Zabin et al., 2022; Du et al., 2024; Lai et al., 2025).

Combined, these studies show that AI/ML can enhance local performance metrics, including the accuracy of predictions, time of review or scheduling effort, and can assist in making a project safer and more efficient when properly implemented (Kineber et al., 2024; Regona et al., 2022). Meanwhile, some of the reviews emphasize that a lot of the evidence is the result of pilot projects, simulations or laboratory conditions, which are specific to a task or phase, and relies on small datasets (Adamantiadou and Tsironis, 2025; Datta et al., 2024; Regona et al., 2023). Enterprise systems and PMIS integration is often reported as a rare feature (Chen et al., 2025; Regona et al., 2023; Tian et al., 2025). Therefore, although the evidence regarding the potential of AI and ML to contribute to performance gains in specific processes is growing, there is no strong empirical data on the role of AI/ML-enabled PMIS in influencing the overall project and organisational performance in real construction contexts. This underlines the necessity to consider the combination of not only the technical feasibility but also the system-level integration and organisational conditions in Finnish construction (RQ1, RQ2).

2.7.3 Implications for evaluating AI/ML-ready PMIS

The analysed literature suggests that AI and ML may be employed to attain the success of the project and PMIS when they can provide valid decision support in many areas, such as scheduling, cost forecasting, risk assessment and document management. Nevertheless, the majority of the reported effects are associated with specific models or tools instead of project management information systems. It can be utilized in this thesis in two main ways to the preparation of AI/ML of PMIS.

First of all, AI/ML-ready PMIS cannot be judged only by their tech-nical complexity, i.e. the possibility to include some algorithms or interface elements, but the extent to which AI capabilities will help to optimize decision-making and performance based on the established criteria of success. The question whether AI-driven features can help project teams, identify risks earlier, build more realistic schedules and budgets, spend less time on routine information processing, and increase transparency and traceability to owners and other stakeholders is involved (Fridgeirsson et al., 2023; Jahanger et al., 2021). This, in relation to PMIS, also covers classical measures of success such as information quality, system quality, use and user satisfaction up to AI-driven functionality.

Second, the evaluation should take into consideration usability, integration and learning. According to Almeida et al. (2025), an AI tool in project management must be evaluated based on its predictive accuracy as well as its usability, integration with other systems and its role in organisational learning. Similarly, Chen et al. (2025) and Nenni et al. (2025) also point out that most of the literature is concerned with technical feasibility, whereas system-level integration, governance, and long-lasting impacts on decision-making and performance have a limited presence in the literature. According to Holmström (2022) and Felemban et al. (2024), the issue of AI readiness is the alignment of technologies with organisational procedures, data sources, the desire of leaders and human capabilities, and not simple purchases of algorithms.

In the case of Finnish construction organisations, it means that the project managers and planners are likely to evaluate the AI/ML preparedness of their PMIS based on the perceived usefulness of AI functions in meeting their project goals, the ability to inte-grate AI functions with current workflows, and the amount of trust and control they have over AI-assisted decision-making. Under the conditions of outlining the readiness and de-development requirements in the interviews (RQ2), the technical and data aspects will then be combined with the attitudes toward project and PMIS success contribution. The contribution of AI-enhanced PMIS to the success of projects and PMIS is viewed as one of the important aspects of AI/ML readiness along with organisational, technical, data and governance. This dimension subsequently comes to be known as the alignment of AI/ML capabilities with project and PMIS-related success and is united with the other dimensions in Section 2.7, where AI/ML readiness of PMIS is conceptualised as a multi-dimensional concept that informs the empirical analysis.

2.8 Summary of the literature and identified research gap

2.8.1 Summary of key themes

Section 2.1 demonstrated that PMIS are perceived as digital systems, or combined systems, in support of the planning, monitoring and control of project-based organisations. Examples of PMIS and project web platforms in construction include documentation and communication and are linked to increased access to information and transparency and in other instances, enhanced time and cost performance, particularly when digital information management underpins control and record-keeping on behalf of owners (Jahanger et al., 2021; van Besouw and Bond-Barnard, 2021; Regona et al., 2022). Meanwhile, PMIS landscapes are still disjointed, and the data is distributed among various tools and lacks sophisticated analytics (van Besouw and Bond-Barnard, 2021; Regona et al., 2022).

Section 2.2 surveyed AI and ML in project and construction management. Research indicates promising applications in PM areas of knowledge, especially in schedule, cost and risk management, as well as in construction-related areas, including safety monitoring, progress tracking and document analysis (Abioye et al., 2021; Lai et al., 2025; Tian et al., 2025; Moon et al., 2022; Li et al., 2024). Nevertheless, the literature is disrupted and is concentrated mainly on model-level performance and standalone tools (Bento et al., 2022; Zabala-Vargas et al., 2023; Regona et al., 2023).

Readiness and adoption in organisations were addressed in Section 2.3. Technological, organisational and human capabilities are identified as critical drivers of generic AI readiness (Holmström, 2022; Felemban et al., 2024; Jöhnk et al., 2021), and construction specific research identifies competitive pressure and efficiency needs as drivers and low digital maturity, cost, limited skills and conservative culture as barriers (Regona et al., 2022). PMIS and AI can be regarded as socio-technical systems the success of which is determined by the correlation of tools, process and people.

Section 2.4 was concerned with data and technical preparedness. BIM and IFC offer highly detailed project information that is structured, yet the extraction, standardisation and integration to AI applications is difficult, and the readiness of data has been rated as average (Zabin et al., 2022; Du et al., 2024; Rane, 2023). The unorganized data contained in work orders, emails, and documents is an important yet underutilized resource, and recent studies on NLP and RAG show how this data can assist in decision-making provided that they are stored and are available through appropriate systems (Ding et al., 2022; Moon et al., 2022; Li et al., 2024; Wu et al., 2025).

Section 2.5 looked at governance, trust and change management. Issues of transparency, reliability, safety and privacy are some of the reasons AI is not embraced in the construction industry, with some advocating lifecycle-aware, trustworthy AI regulation, such as explainability and transparent accountability (Yang et al., 2025; Tian et al., 2025). The importance of ethical considerations is highlighted as one of the foundations of AI in project management, and some of the success factors in organisations are strategy, leadership, data governance, workforce capabilities and culture (Hughes et al., 2025; Wuni, 2025; Regona et al., 2022).. The skills gaps, insufficient training, and social factors of the AI appropriation also support the necessity of organization-based capability development (Müller et al., 2024; Lemos et al., 2025; Felicetti et al., 2024; Regona et al., 2022).

Lastly, Section 2.6 suggested that AI and PMIS will help to make projects and PMIS successful by enhancing predictive capabilities, identifying risks earlier, executing information processing and enhancing its visibility more effectively (Fridgeirsson et al., 2023; Zabala-Vargas et al., 2023). However, empirical data on long-term, system-level effects of AI/ML-enabled PMIS on the outcomes of a project in real construction practice is still nascent and frequently relates to pilot or simulation studies (Datta et al., 2024; Adamantiadou and Tsironis, 2025; Regona et al., 2023).

2.8.2 Identified gaps in the existing literature

In these themes, a number of gaps emerge that inspires this thesis. First, PMIS as AI/ML platforms in construction do not have a system-level focus. The literature on PMIS highlights fragmentation, heterogeneity in terms and a lack of clarity regarding PMIS capabilities and architectures (van Besouw and Bond-Barnard, 2021; Regona et al., 2022), whereas AI in construction and AI in project management research treat AI tools as black boxes, seldom considering how to connect them to project information systems or digital platforms (Chen et al., 2025 According to Bento et al. (2022), there is limited literature that discusses the adoption of AI on the level of project management systems or methodologies.

Second, readiness dimensions tend to be dealt with independently as opposed to being integrated. The technological, organisational and human capabilities are defined by generic AI readiness frameworks (Holmström, 2022; Felemban et al., 2024; Jöhnk et al., 2021), whereas construction-specific work approaches data quality, BIM data preparation, fragmented systems and skills as obstacles (Du et al., 2024; Datta et al., 20 A different set of studies deals with governance, ethics and trust (Yang et al., 2025; Hughes et al., 2025; Tian et al., 2025). Only a few studies integrate technical/data, organisational, governance and performance perspectives into a multi-dimensional, holistic, view of AI/ML readiness at the PMIS level.

Third, the combination of AI/ML and PMIS in the construction practice is under-researched and limited. Various AI/ML applications are prototypical or task-oriented risk analysis, scheduling, cost estimation or document checking (Abioye et al., 2021; Lai et al., 2025; Moon et al., 2022; Li et al., 2024). Several reviews conclude that the integration with enterprise information systems and project management platforms are uncommon and that AI tends to be used on single datasets (Chen et al., 2025; Regona et al., 2023; Tian et al., 2025). The demands of platform-based, lifecycle-oriented solutions and the integration of AI into project information systems are the signs of a new yet not fully-developed research direction (Tian et al., 2025; Regona et al., 2023; Nenni et al., 2025).

Fourth, there is limited empirical evidence of relationships between AI/ML-enabled systems and project and PMIS success. Though smaller-scale studies on the impact of AI-enabled PMIS on project time, cost, quality, safety and stakeholder satisfaction show encouraging results, larger-scale, longitudinal studies are less common (Datta et al., 2024; Adamantiadou and Tsironis, 2025; Chen et al., 2025). The standards used to evaluate AI tools are frequently based on the performance of the model, but not on how well the system is integrated or how usable it is to the organisation or how it supports organisational learning (Almeida et al., 2025).

Fifth, the literature on practitioner-oriented, context-specific research examining the perceptions of project managers and planners regarding AI/ML preparedness and development requirements of their PMIS, especially in Finnish or Nordic construction, is limited. A number of reviews recommend more practice-based studies on the issue of adoption, governance, and human-AI collaboration in the construction industry (Regona et al., 2022; Datta et al., 2024; Chen et al., 2025). According to Felicetti et al. (2024), the study of generative AI in project management is at the embryonic level and that managerial approach to adoption is under-researched. This, combined with the insights on drivers and barriers that are specific to construction organisations (Regona et al., 2022; Shang et al. (2023) et al. 2023a), suggests a definite gap in the empirical research in particular national settings like Finland.

These gaps ground the purpose, research questions and objectives of this thesis: to review AI/ML preparedness factors on the level of PMIS and to investigate the perception of the practitioners in Finnish construction regarding the preparedness and development of their project information systems (RQ1, RQ2).

2.8.3 Conceptualisation of AI/ML readiness of PMIS and implications for this thesis

From the literature review conducted in sections 2.1 – 2.6, AI/ML-readiness of project management information systems in this thesis is considered a multifaceted concept. It represents the degree to which PMIS and its organizational environment are equipped to accept, implement, and profit from the functionality of artificial intelligence and machine-learning. Five interconnected dimensions were highlighted within the literature.

1. Organizational environment for AI/ML in PMIS

The preparation of AI requires a strategy, leadership dedication, resources, skills and culture (Holmström, 2022; Jöhnk et al., 2021; Felemban et al., 2024). This includes ex-plicit AI tactics, strong top-management support, adequate financial and techno-logical resources, and organisational cultures that promote experimentation and learn-ing in construction (Wuni, 2025; Regona et al., 2022; Lemos et al., 2025). In PMIS, the organisational dimension determines the existence of strategic intent, governance structures, knowledge management practices and labour potential which project-based organisations in Finnish construction require to create and use AI-enhanced PMIS (Khan et al., 2024).

2. Technical and integration capabilities of PMIS and related systems

To be ready for AI, PMIS need architectures that enable them to combine and integrate data from various sources (e.g., schedules, BIM, cost systems, site-apps), as well as connect to AI-service providers via suitable interfaces (van Besouw & Bond-Barnard, 2021; Regona et al., 2022). Technical readiness includes system modularity, compatibility with BIM and other systems, API or connector availability, and the ability to host or link AI-modules for tasks like scheduling, risk-analysis or document-review (Rane, 2023; Chen et al., 2025; Al-Sinan et al., 2024).

3. Availability, structure, and access to project and document data

AI and ML require sufficiently large amounts of high-quality data in suitable formats. Structured machine-readable data can be obtained by using BIM and IFC, however, modelling is often inconsistent and few tool-chains are available to perform AI-ready extraction (Du et al., 2024; Zabin et al., 2022). Moreover, construction projects generate large quantities of unstructured text in specifications, contracts, work-orders and safety-reports, which present both challenges and opportunities for NLP-based applications (Li et al., 2024; Ding et al., 2022; Moon et al., 2022). Therefore, the data-readiness at the PMIS level encompasses the extent to which project and document data are collected, standardized, connected and made available for AI/ML use, including through centralized repositories and consistent metadata (Zabala-Vargas et al., 2023; Jahanger et al., 2021).

4. Responsible and accepted use of AI Governance, trust and change management arrangements.

Construction needs trustworthy AI that necessitates lifecycle-related governance, planning, data collection, algorithm development, deployment, maintenance and archiving (Yang et al., 2025). In the case of PMIS, this dimension includes data governance, model validation, approval processes, logging, responsibility of the AI-assisted decisions, and error or bias management mechanisms (Tian et al., 2025; Hughes et al., 2025; Regona et al., 2022). It also comprises change-management practices, training, AI literacy and social influences that determine the way project managers and project planners are actually appropriating AI features integrated within PMIS (Muller et al., 2024; Felicetti et al., 2024; Wuni, 2025; Rane, 2023).

5. Alignment of AI/ML functionalities with project and PMIS-related success

Lastly, AI/ML preparedness entails a clear connection between the perceived AI functionalities and enhancements in project and PMIS success. With AI-enhanced PMIS, project teams are expected to attain a superior time, cost, quality and safety performance and assist in making clearer and informed decisions (Fridgeirsson et al., 2023; Jahanger et al., 2021). The criteria of evaluation thus consider both model accuracy and usability, integration with the existing workflows and contribution to organisational learning and control (Almeida et al., 2025; Chen et al., 2025; Nenni et al., 2025).

These five dimensions are not a formal named framework proposed in this thesis, but are a working conceptualisation of AI/ML readiness of PMIS. They integrate knowledge on PMIS studies, AI in project and construction management, AI preparedness studies, data and technical basis, and governance and success literature.

The conceptualisation has two main implications for the study. In the case of RQ1, it offers a framework under which the systematic literature review can be interpreted: the factors determined in the existing literature are plotted onto these dimensions to determine the current level of AI/ML preparedness of PMIS in construction. In the case of RQ2, the dimensions are used to sensitise the empirical study of the Finnish construction practice: they are used to design interview questions and to guide the thematic analysis of how the project managers and planners define the current use, readiness and development needs of their PMIS.

This multi-dimensional notion of AI/ML preparedness of PMIS offers a consistent perspective on the extent to which existing systems in the Finnish construction are ready to integrate and take advantage of AI and machine-learning capabilities, in accordance with the thesis title, research questions and objectives. In the following chapter, the research methodology applied to carry out the systematic literature review and semi-structured interviews based on the analysis is described.

3 Methodology

3.1 Research approach

This thesis uses a qualitative research design. A qualitative research design is appropriate here since the focus of the study is not to test a specific technological tool or evaluate one single variable. Rather, the goal of the study is to identify how AI & Machine Learning Readiness of Project Management Information Systems is conceptualized within Research and how it is perceived by the Practitioners in Finland's Construction Industry. In addition to being a technical aspect of readiness, it has many other related aspects such as Data Quality, System Integration, Organizational Support, Trust, Governance and how Project Professionals utilize Information Systems on a day-to-day basis. Therefore, due to the fact that readiness will be examined as a socio-technical condition and not just as a purely software related question (Jöhnk et al., 2021; Felemban et al., 2024) a qualitative research design will be most suitable to analyse the above mentioned empirical purposes of the thesis. Furthermore, the qualitative research design corresponds to the empirical objectives of the thesis. The interview-based study aims at collecting views from Project Managers, Planners and Similar Professionals who utilize digital project tools and project information in Finland's Construction Industry. The primary objective of the study is to understand how those practitioners describe today's roles of PMIS, which are the major barriers preventing them from using AI and Machine Learning, and what types of developments do they see necessary in today's PMIS. In this manner, the focus of the study is upon practical perceptions and experiences instead of statistical generalization. Finally, based upon the overall logic of the thesis, a qualitative research design also corresponds to chapter 1 where the central problem is defined as the limited knowledge regarding how prepared today's PMIS in Finland's Construction Industry are for AI and Machine Learning. In turn, Chapter 2 defines readiness as a multi-dimensional construct consisting of Technical, Organizational, Human and Governance-related aspects. Due to the fact that the study wants to examine how those dimensions occur in Practice, a qualitative research design provides an appropriate framework for analysing practitioner views relative to the Conceptual Foundation developed via Literature Review.

3.2 Research design

In addition to providing an appropriate methodology for answering the research questions, the systematic literature review and the empirical interview study are also based on the aims and objectives of the thesis. The systematic literature review addresses Research Question 1 (RQ1) by using systematic methods to evaluate how PMIS, AI and Machine Learning have been discussed and analysed in previous studies and how the main aspects of AI and ML-readiness of PMIS were synthesized. The empirical interview study uses semi-structured interviews with project managers and planners in Finnish Construction to answer Research Question 2 (RQ2). Project managers and planners will be asked about the current degree of Readiness of their own PMIS, as well as the most important aspects they consider to be necessary for future development in relation to AI and ML. Both studies together form the complete basis for examining the Readiness of PMIS from both scientific and practical perspectives.

The purpose of the systematic literature review is to establish the conceptual background of the present study. It does not only summarize previous studies, but also identifies characteristics of AI/ML-readiness of PMIS as well as organizes them in a working framework which can be used for further analyses. The empirical part of the research includes semi-structured interviews with Finnish Construction professionals. These interviews should explore among others, how PMIS are used in practice, what kinds of problems Finnish Construction professionals encounter when integrating different types of data in their PMIS, how Finnish Construction professionals view support systems and rules governing the use of their PMIS, and how likely they think it is that functions related to AI would be implemented in their PMIS in their daily project work. Therefore, the interview-study completes the literature-review by including practical experiences of persons who work with project information in their everyday organizational routines.

Thus, the dual nature of the present research-design has its strength in supporting each component. The literature review establishes a conceptual basis for understanding what readiness might include; whereas, the interview study provides examples from current practices in Finnish Construction how these issues appear. Therefore, the dual nature of the design enables the present thesis to go beyond a purely theoretical description of the readiness issue or a pure descriptive report on the experiences of practitioners. Figure 3.1 illustrates the overall research design of the study and shows how the systematic literature review and the empirical interview study were used together to address the research questions through an integrated interpretation.

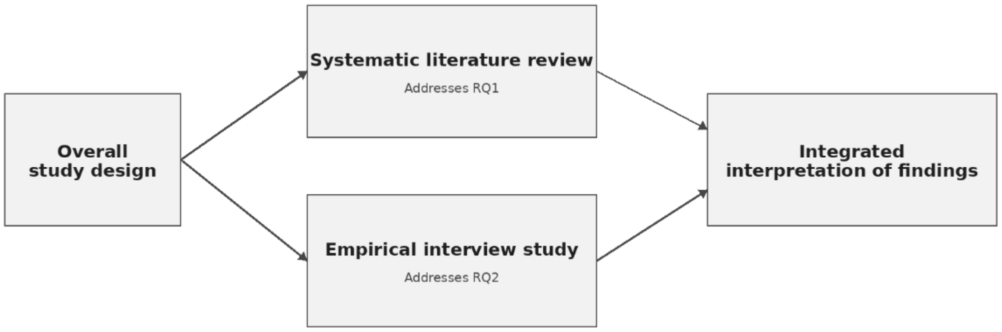

Figure 3.1 Overall research design of the study.

3.3 Systematic literature review process

The purpose of conducting this systematic literature review was to provide answers to RQ1 and to determine the factors that define the AI and machine-learning preparedness of project management information systems in project and construction contexts. The review was conducted in a chronological order through the definition of the focus of the review, identification of studies, selection of studies, full text evaluation and synthesis of the results. The selection of focus of the review was based on the thesis research questions and objectives. The University of Vaasa Library and Tritonia interfaces were used to search the literature using the following databases and publisher platforms: Scopus, Web of Science, EBSCO, ScienceDirect, Emerald Insight, Wiley Online Library, and IEEE Xplore. The primary search was in the past 2021-2025, but older methodological and foundational works published before 2020 were only included where required to aid the theoretical or methodological contextualization of the thesis. The search was conducted with the help of combinations of the keywords associated with PMIS, AI/ML, readiness, construction, data, and integration. The key search terms were, e.g., project management information system* AND construction AND (“artificial intelligence” OR machine learning) PMIS AND readiness AND construction, (project management information system* OR PMIS) AND (AI readiness) OR (organisational readiness) OR adoption), and (construction OR construction project management) AND (machine learning) AND (integration OR governance OR trust OR data). Further searches were done with the related keywords, which include, BIM, IFC, project data, data readiness, systems integration, governance, trust, and change management. The inclusion criteria were narrowed to peer-reviewed journal articles, publications in the English language, studies that directly addressed PMIS, AI, machine learning, readiness, adoption, technical or data readiness, governance, trust, or change conditions that addressed PMIS readiness, and studies that were in a project management or construction management or a setting closely related to digital project-information. The exclusion criteria were non-peer-reviewed, non-English, and studies not directly related to PMIS or project-information environment, studies not theoretically relevant to PMIS readiness, and duplicate records, and studies whose conclusions did not add new analytical value to the already covered ones. The screening was done in phases. To begin with, there were 214 records identified by searching databases and platforms. Following the removal of duplicates, 176 records were left. Abstract and title screening narrowed the list of records to 74 to be accessed in full-text. After the full-text analysis based on the inclusion and exclusion criteria, 46 studies were included in the final synthesis. The latter group of articles was subsequently compared to each other with the aim of extracting common readiness-related issues as well as to establish a common framework that can be used to interpret the results of the interviews. The synthesis led to a multidimensional preparedness model comprising of organisational context, technical and integration capabilities, project and document data, governance and trust, and alignment with project and PMIS success.

3.4 Empirical interview study

The practical part of this research was a qualitative interview study among the personnel employed at the firms engaged in construction projects in Finland. This study's aim is to answer RQ2 as it describes what practitioners state about the current usage of Project Management Information Systems (PMIS) and their readiness for Artificial Intelligence (AI) and Machine Learning (ML), as well as, their perceived needs for PMIS development. Literature Review has created theoretical basis for this study; whereas, the qualitative interview study provides data from practice that is required to evaluate how these questions are presented in an actual project environment.

3.4.1 Interview design and participants

The empirical section of the research was a one to one semi-structured interview with construction professionals operating in Finland. The use of semi-structured interviews was suitable as it gave the researcher a chance to discuss a set of themes that all participants addressed and gave the researcher a chance to seek clarification in case of doubts and to use practical examples (Roulston and Halpin, 2022, p. 677). This approach proved appropriate to the current research since PMIS preparedness to artificial intelligence and machine learning is impossible to be perceived successfully with the help of fixed-response questions. Rather, it asks the participants to write about how the systems, data, workflows, routines, and project practices work in daily work.

The four central themes of the interview guide were PMIS and digital tools applied in the daily project work, data quality and data integration, organizational usage and support, and the potential uses, conditions and risks of AI/ML. This design promoted uniformity throughout the interviews and at the same time gave the respondents the opportunity to narrate their personal work experiences. The interview questions included the nature of PMIS and project platforms in practice, how the tools and data sources interact, the quality of data and the potential of AI/ML, the extent to which organizations support and regulate the use of AI/ML, and the perceived benefits and risks of applying AI/ML to the existing PMIS environment.

Purposive sampling was used to select the participants. There was no goal of statistical representativeness but only the desire to get informed practitioner views on the existing use of PMIS and their readiness to AI and machine learning in Finnish construction. The target group was consequently the project managers, planners and other professionals with experience working with digital project tool and platforms within the Finnish construction settings. The choice of logic was in line with the study focus. Since the thesis focuses on the existing PMIS utilization, preparedness requirements, and the development requirements concerning AI/ML, the respondents were selected based on their practical knowledge of project-information systems, digital workflows, and construction project coordination. Table 3.1 summarizes the anonymized participant roles, types of organizations and the length of the interviews.

Table 3.1 Overview of interview participants

Participant ID	Role	Organisation type	Interview duration
INT01	Group manager with responsibility for project management and scheduling	Construction	65 min
INT02	Director	Construction	60 min
INT03	Project coordination professional	Construction	70 min
INT04	Site-based construction professional	Construction	60 min
INT05	Construction engineer with consulting and supervision experience	Consultant	60 min

INT06	Construction management professional	Consultant	90 min
INT07	Construction consulting professional	Consultant	60 min
INT08	Construction professional in a multi-system project environment	Construction	60 min
INT09	Project manager	Construction	60 min

Note. The table presents anonymized background information on the interview participants. Organization types are reported broadly in order to preserve confidentiality.

3.4.2 Data collection

The interviews took place remotely via Microsoft Teams or Zoom from 2 March 2026 to 31 March 2026. The interviews were conducted in English and each interview took about 45 to 60 minutes. Nine (9) interviews were achieved out of 42 possible respondents who were contacted via email. The resulting interviews created a small and narrow qualitative data set which examined themes prevalent, areas of divergence of emphasis and pragmatic perceptions of what is needed and what is ready to develop. Participants gave their consent to have their interviews audio recorded. Their respective audio recordings were then transcribed after this agreement. Quality checks were then done on the produced transcripts which was later imported into NVivo to be analysed. Participation was made voluntary, to entice the participation and also ensure that the anonymity of the participants was maintained. Any respondent had the right to refuse to answer any question during the interview process at any time and they were free to pull out during the interview. Moreover, rather than mentioning the name of a participant or company in the body of the thesis, participants were mentioned using general professional terminology. These steps helped in achieving consistency in collection of the information as well as ensuring the identity of the subjects was not compromised. The interview guide was applicable in all interviews but flexibility was applied in regard to asking additional questions in case a respondent needed more clarification or in desiring to provide examples..

3.5 Data analysis

There were two analytical elements in the study which are related. To begin with, the systematic literature review was synthesised to create a list of readiness dimensions on which the conceptual foundation of the study was built. Second, thematic analysis was done to the interview data with the help of NVivo. The readiness dimensions based on literature were then employed as sensitising concepts in the understanding of how Finnish construction practitioners explained the current use of PMIS, AI/ML readiness, and development requirements. The defined studies in the literature-based component were critically reviewed against each other to reveal recurrent readiness-related issues. Its purpose was to shift away on an individual basis to a more systemic conceptualization of the AI and machine-learning preparedness of PMIS in projects and construction settings. This synthesis led to five broad dimensions namely the organisational context, technical and integration capabilities, project and document data, governance and trust, and alignment with project and PMIS success. The empirical part involved the recording of the interviews, which were transcribed and cleaned and fed into NVivo. The initial analysis phase was familiarisation whereby transcripts were read repeatedly in an effort to get a general idea of what was contained in the transcripts before formal coding commenced. The interview data was stored, organised, retrieved, and coded with the help of NVivo, but the analysis and interpretation were the prerogative of the researcher (Bazen et al., 2021, p. 244). The relevant segments of the interview material were coded in relation to the research questions and issues which arise out of the data in an iterative manner after familiarisation. To document the codes, their meanings, and how they related to each other throughout the interview data, a codebook was constantly updated and revised (Saldaña, 2016, pp. 27–28). Duplicate or ambiguous codes were consolidated, explained, renamed or stabilised where appropriate. The finalised codebook was subsequently summarised into five more advanced themes, which the results chapter was organised under.

The readiness dimensions derived in the literature served as a theoretical framework to interpret the themes of the interviews in the last analytical step. This has enabled the empirical results to be debated against the existing literature and yet be based on the testimonies of the participants. The Copilot-assisted coding was also used on the same data of the interviews after the thematic analysis using NVivo had been conducted. This was only a supportive comparison and not a substitute for the main researcher-led analysis. Thematic analysis with the assistance of NVivo was the primary analytical centre of the study, and the Copilot-aided coding was a mere comparison. Figure 3.2 outlines the major steps involved in the data analysis process which will be adopted in the current study and can be summarised as follows: synthesis of the literature review, development of the readiness dimensions, transcript familiarisation, coding, codebook refinement, theme development and integrated interpretation.

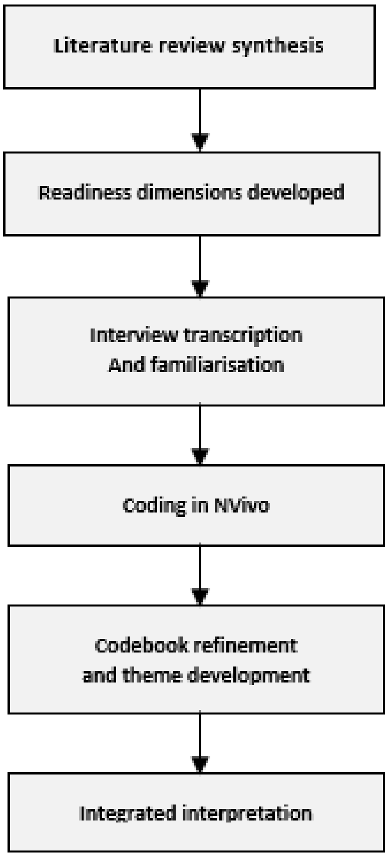

Figure 3.2 Data analysis process used in this study.

3.6 Trustworthiness of the study

The research was considered in terms of validity in terms of credibility, dependability, confirmability and transferability. This was done in order to provide credibility and through an active dialogue between the literature and the materials in the interviews. The transcribed interview texts were read several times in the first phase of familiarization and coding during the empirical phase of the research to remain in close touch with the material before and after interpretation. Iterative coding procedures, the recurring examination of coded passages and comparative analysis across all the interviews were used to establish the final themes. In this way, it can be concluded that the empirically de-rived interpretations of the participants accounts have been maintained in their own voices. Dependability was achieved via a well-defined and consistent methodology. Chapter 3 determines the research design, which is a systematic explanation of the process of conducting the literature review, the design of the interview, ways in which data would be collected and analysed, and the key stages of analysis. The repetitive procedure of the coding in the empirical analysis enabled the further re-fining of the codebook; finally the stable thematic framework was outlined before the Results chapter was written. These actions improved the transparency of the analytic process and minimized unneeded instability in the coding scheme.

The degree to which the interpretations remain true to the original data (confirmability) has been supported through maintaining strong ties between the interpretation and the actual data. NVivo was utilized to assist in organizing, storing, retrieving, and coding of the interview data; however, NVivo does not take responsibility for the analysis or interpretation (Bazen et al., 2021, p. 244). In addition, a codebook was created and continuously updated throughout the analysis so that records could be maintained regarding what each code represented, its significance, and relationship(s) among them across the entire set of interviews (Saldaña, 2016, pp. 27 – 28). The eventual themes produced were based upon repeated examination of the coded material and comparative analysis across interviews thereby establishing a clear linkage between the empirical data and conclusions drawn from such.

Transferability was facilitated with the description of the Finnish concrete construction setting that the research was carried out in, the general professional description of the roles of the participants, the description of the setting of the interview, and the description of the general analytical procedures used. According to Drisko (2025), qualitative studies demand having thick descriptions in order to be able to make transfers. Although the aim of this thesis was not statistical generalizability, the purpose of the study was to create a contextualized explanation of PMIS readiness in Finnish construction that could be applicable to other similar project and organization contexts. Furthermore, a subsequent comparison of the manual NVivo coding with a Copilot-assisted coding of the identical interview material was utilized as a supportive check in analysis. The aim of this comparison was to investigate the claim that the overall thematic patterns did not vary widely between two coding procedures. It was not to substitute the main human-based analysis but offered another means of evaluating the consistency of the major interpretations.

3.7 Ethical considerations

This interview research was voluntary. All participants were informed of the nature of the research beforehand; general topics that would be covered in the interviews; and how the arrangements of the interview would be. The participants were also encouraged to consider that in the case there were questions that they did not want to answer, they could do so. Participants were informed of these conditions both in the invitations to interview and in their guides to questions that they were going to be interviewed under. Interviews were recorded only with the permission of the participants. All the recordings that were made were limited to authorized subjects of this study. The name of any participant or company name has not been mentioned in the body of this thesis. Instead of making a direct reference to participants (with names included), the participants were generally referred to as professionals. This approach was used because this was an attempt to reduce the possibility of identifying individual participants by referencing to their professional descriptions, and at the same time, made it possible to report meaningfully on the empirical evidence. As part of the research study no confidential company information has been sought. The interviews were centred on experiences, views and practical perceptions of each of them on use of project management information systems; availability of information pertaining to project; support given to project teams by organisations; and development requirements of artificial intelligence and machine learning. The data of the interview was considered as research data of the study and thus presented anonymously.

3.8 Chapter summary

Chapter 3 explained the methodological basis of the thesis. It described the two-part design consisting of a systematic literature review and an empirical semi-structured interview study, and it outlined how the literature and interview material were analysed through literature synthesis and NVivo-supported thematic analysis. The chapter also clarified how trustworthiness and ethical considerations were addressed. On this methodological basis, Chapter 4 presents the results of the study.

4 Results

This chapter presents the findings of the study. It first summarizes the literature-based readiness dimensions used as the analytical framework and then reports the interview findings from Finnish construction. The chapter ends with a cross-theme synthesis of the current PMIS readiness profile. Section 4.1 starts with a brief synthesis of the literature-based dimensions of readiness that were developed in Chapter 2 and utilizes them as the analytical framework to interpret the empirical content. The findings of the interview with Finnish construction are then presented in section 4.2 in five final themes. These results are arranged by theme and not question by question in order to enable the chapter to provide a coherent description of the key trends that take place throughout the data. Section 4.3 is used to synthesize these findings by a brief cross-theme review of the existing readiness picture of PMIS in Finnish construction. A subsequent section, 4.4, makes a comparison of the manual NVivo coding and the Copilot-assisted coding to determine the extent of convergence between the two analytical methods as well as to consider the implications of these methods to the interpretation of the results. This general framework maintains Chapter 4 result-oriented and also sets the stage towards subsequent large interpretation in Chapter 5. Table 4.1 provides an overview of how the five final themes are distributed across the nine interview cases and is used to show the spread of coded references across the dataset.

Table 4.1 Distribution of coded references across the five final themes and interview cases

Final theme	**INT01**	**INT02**	**INT03**	**INT04**	**INT05**	**INT06**	**INT07**	**INT08**	**INT09**
T1	**14**	**7**	**3**	**14**	**8**	**11**	**10**	**11**	**5**
T2	**12**	**8**	**6**	**3**	**5**	**9**	**13**	**15**	**5**
T3	**15**	**6**	**16**	**0**	**1**	**0**	**10**	**8**	**6**
T4	**8**	**4**	**13**	**8**	**4**	**8**	**14**	**4**	**5**
T5	**13**	**11**	**13**	**9**	**11**	**6**	**11**	**9**	**5**

Note. T1–T5 are shortened theme labels used for readability: T1 = Fragmented PMIS and weak system integration; T2 = Formal PMIS use and informal project communication; T3 = Trustworthy, structured, and governable project data; T4 = Organizational routines, support, and workflow fit; T5 = Current AI use in limited support roles. The table shows the distribution of coded references across the five final themes and the nine interview cases and is intended as an overview of thematic coverage rather than as a measure of analytical importance.

4.1 Literature-based readiness dimensions: brief synthesis

Chapter 2 formulated a conceptualisation of AI/ML preparedness of PMIS on a multi-dimensional level. Instead of taking readiness as a technical issue, the literature analysis revealed that it should be conceptualized in multiple dimensions that interact to define, in the first place, whether existing project information systems can be used to implement AI and machine-learning capabilities in practice. These dimensions are applied in the current chapter as the frame of analysis of the interview results of Finnish construction. The synthesis based on the literature identifies five dimensions of readiness. The former is an organisational context and workflow alignment, which focuses on the fact that the AI/ML readiness is not a matter of technology, but of organisational and human conditions. The second is technical and integration capabilities, which relate to the system architectures, interoperability, and digital connections, by which PMIS can support more sophisticated functions. The third is related to the readiness of project and document data, such as the quality, structure, and availability of the data whose use would be based on AI/ML. The fourth deals with the conditions of governance and trust, such as transparency, responsibility, and control of data and trust in AI-generated outputs. The fifth is related to alignment to project and PMIS-related success, i.e. AI/ML readiness can only be meaningful to the extent that it can be used to support accepted project and PMIS performance thresholds. These dimensions combined offer a brief conceptual point of departure of the reading of the empirical material in an organized fashion.

These literature-based readiness dimensions are correlated with the five ultimate themes of interviews in Table 4.2. It does not intend to substitute the thematic analysis given later in Section 4.2, but it is aimed at clarifying how the empirical results can be construed vis-a-vis the conceptual preparedness framing that has been developed based on the literature review. Through this, the table serves as the analytical linkage between Chapter 2 and the results of the interview that comes after.

Table 4.2 Literature-Based Readiness Dimensions and Their Main Links to the Final Interview Themes

Literature-based readiness dimension	What the dimension emphasises in this study	Main links to the final interview themes
Organisational context and workflow alignment	Organisational routines, workflow fit, practical use conditions, and the extent to which systems support real project work	**4.2.2** Formal PMIS use and informal project communication; **4.2.4** Organisational routines, support, and workflow fit
Technical and integration capabilities	System architecture, interoperability, integration maturity, and the technical ability of PMIS environments to support advanced functionalities	**4.2.1** Fragmented PMIS and weak system integration
Project and document data readiness	Data quality, structure, consistency, accessibility, and the extent to which project information is usable for AI/ML-related purposes	**4.2.3** Trustworthy, structured, and governable project data
Governance and trust conditions	Ownership, control, permissions, transparency, and trust in	**4.2.3** Trustworthy, structured, and governable project data; **4.2.5** Current AI use in limited support roles

	data handling and AI-supported outputs	
PMIS usefulness / success alignment	Whether AI/ML-related PMIS development supports accepted project and PMIS performance needs in practice	**4.2.2** Formal PMIS use and informal project communication; **4.2.4** Organisational routines, support, and workflow fit; **4.2.5** Current AI use in limited support roles

4.2 Thematic interview findings from Finnish construction

This part provides the interview results of Finnish construction. According to the analytical style of the research, the results are structured with five conclusive themes as opposed to the question-by-question reporting format. This thematic framework allows demonstrating the bigger patterns of meaning that arise within the dataset of the interviews and connecting them to the literature-based dimensions of readiness that are summed up in Section 4.2. This section is thus not merely aimed at reporting participant opinions but giving a systematic report of how the current PMIS adoption, AI/ML preparedness and needs of development are articulated in the actual sense. The results are stated in the subsequent subsections using the five final themes.

4.2.1 Fragmented PMIS and weak system integration

Throughout the interviews, the current PMIS in the Finnish construction sector was seldom mentioned as a unified platform that would unite project information in a seamless manner. Rather, respondents described the project information management as a stratified and partially-linked environment made up of various tools, data stores and re-porting views, each of which fulfills a particular purpose but seldom constitutes a complete unit. This implies that fragmentation is not a small exception or an infrequent technical inconvenience, but a normal state in the daily project work. Even though digital tools were evidently present and even fulfilled key tasks like reporting, documentation, and visibility, their co-existence was not yet a system environment that was consistently integrated. Consequently, the project data tended to be dispersed in different applications and processes, thus, becoming more difficult to relocate, integrate, and utilize in a consistent and reliable manner. Regarding readiness, this is important as the usefulness of this or that higher level of PMIS functionality hinges not only on the availability of digital tools, but also on the possibility of information flow between them to be consistent and reliable enough.

Project data is spread across many tools

One common theme was that the participants did not identify a single PMIS in the strict sense, but as a group of systems that, when combined, facilitated project work. One respondent mentioned that the project environment was a combination of many tools (INT08), and another mentioned that PMIS is a combination, and not a single software (INT09). Practically, these combinations comprised ERP, document systems, scheduling systems, reporting views, Excel files, project banks, and project- or client-specific platforms. It was not a lack of digital support, but the fact that project information needed to be pieced together by a number of environments and each provided only a portion of the total information required. This rendered the pro-project information setting more extensive than any specific system, and, simultaneously, more challenging to deal with as a reliable whole.

Manual transfer and duplicate work remain common

The work to maintain systems aligned also exhibited fragmentation. Respondents used over and over again information flowing through copy-pasting, file-exporting, links, PDFs, spreadsheets, and manual entry repeatedly. INT01 had concisely summarised this mixed environment as follows: You have copy-paste, file exports, integrations (INT01). INT08 and INT09 reported conditions where there were some integrations, but there was still a heavy reliance on copy-paste, file exports, manual inspections and, in some instances, on manual reentry, as transfer was not yet trusted. These descriptions imply that digitalisation has decreased certain types of manual coordination, yet has not eliminated the repetitive involvement to relocate and harmonize the information between systems. Practically, the load frequently manifested itself not so much as a single technical failure, but as a thousand little repetitions, each adding to the cumulative total of unnecessary labor, and undermining belief in the con-sistency of the information produced.

Interoperability is uneven and integration remains incomplete

The interviews were not such as could easily be summed up to a total disconnection of systems. Rather, they mentioned selective and partial integration. Other environments could also integrate the data into reporting tools and some of the transfer routes were already automated. At the same time, respondents continued to report that systems continued to be poorly communicating, that more powerful APIs were still needed, and that there was still some software that they believed was difficult or hard to integrate with. This was expressed particularly by INT01 who noted that APIs were highly handy in places that they were, but that certain software could not be inserted in those places either. The same view might be viewed in INT08 and INT09 who mentioned settings in which some integrations existed, however, manual work needed to be done since the reliability of the system-to-system interaction was not established. The absolute isolation of technicality, however, was not the case, but the infrastructure of partial connectivity, which still meant that project teams had to re-construct an operational whole in different environments. The im-portance of that constraint is as readiness perspective because more advanced PMIS functionality is not dependent upon the simple fact that digital information is in a single place, but on the flow of information between systems at a level of reliability that is satisfactory.

BIM/IFC links exist, but mostly as partial rather than full workflow integration

The BIM and IFC evidence in interviewees was less than the integration issues in general, and should thus be handled more cautiously. It connoted a partial, not wholly assimilated role in the regions it was found. INT01 noted that the IFC models were already commonplace and could be used to support the activities related to quantities and costs in some cases. INT08 also defined BIM and IFC as technical under-understanding tools and occasionally quantities, but also stated that their relationship with schedule, cost, and daily site follow-up was not really robust in the normal project life. A smaller example, backed by INT05, was a come-and-go: some model-based computations could be made but this was not a more general workflow of PMIS functions. It is then concluded with the highest degree of security that BIM and IFC do exist and can be applied to selective technical domains but their overall relationship to the PMIS work processes are few and uneven.

Client-specific platforms add further complexity

A much more narrow yet also applicable extension of this disintegration was on project- and client-specific platform set-ups. In INT05, the same information associated with the invoice was to be entered into multiple programs, not due to the fact that it was the needed information of one internal process, but because the work environment, itself, demanded parallel updating. INT04 provided a supportive illustrative example where client- or company-specific platforms multiplied the updating work and stored the information in different locations. These instances lack the subsection as much as the larger fragmentation pattern, but they support the same argument: in addition to internal system diversity, project work can also be influenced by external platform requirements, which further introduce a dimension of duplication and coordination work.

Collectively, these descriptions lead to the overall assumption that the primary flaw of the present PMIS at this stage is not merely that a vast amount of digital tools is utilized, but that the connections between the tools are not in balance, partly automated, and only partially joined together. Reporting, records, and visibility can be supported with current systems in key areas, but is not yet a coherent enough technical foundation to support the use of more advanced AI- or machine-learning-enabled PMIS without further integration, simplification, and more reliable flows of information. These trends are summarised in Table 4.3 and visualised in Figure 4.1.

Table 4.3 Fragmented PMIS Landscape: Main Integration Problems and Readiness Implications

Pattern in the interview material	Typical manifestation in practice	Main interview support	Readiness implication
Project data is spread across many tools	ERP, document systems, reporting views, Excel, scheduling tools, project banks, and project-specific platforms are used in parallel	INT01, INT08, INT09	Project information often has to be assembled across several environments rather than followed through one clearly unified workflow
Manual transfer and duplicate work remain common	Copy-paste, file exports, links, PDFs, repeated entry, and manual checking across systems	INT01, INT08, INT09	Extra effort is required to maintain consistency, which weakens the dependability and reusability of digital project information
Interoperability is uneven and integration remains incomplete	Some integrations exist, but many connections remain partial, unstable, or absent	INT01, INT08, INT09	Information can be combined in some areas, but overall system coherence remains limited
BIM/IFC links are partial rather than fully embedded	BIM/IFC supports some technical, quantity-, or cost-related tasks, but is not yet strongly linked to wider PMIS workflows	INT01 and INT08, with selected support from INT05	Model-based information is useful in selected areas, but not yet part of one consistently integrated project information flow
Client-platform complexity	The same information may need to be entered	INT05, with supporting	Platform requirements can increase repeated

adds further coordination work	into several programs because of project- or client-specific platform arrangements	illustration from INT04	updating work and make more consistent information handling harder across projects

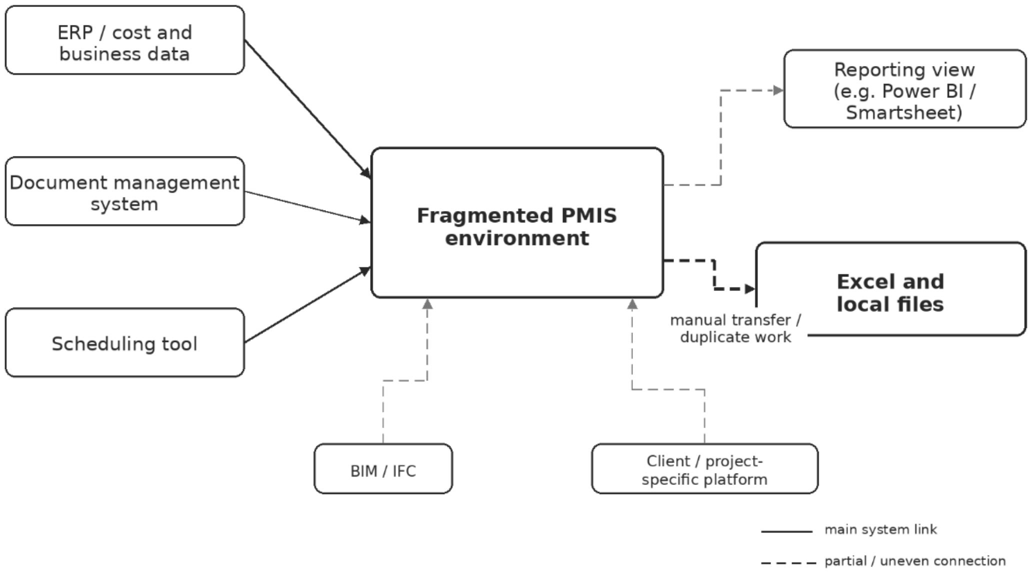

Figure 4.1 Fragmented PMIS landscape and weak system integration in Finnish construction

Figure 4.1. Current PMIS in the interview material was described less as one integrated system than as a partially connected landscape of ERP, document systems, reporting views, spreadsheets, models, and project-specific platforms, with manual transfer and selective integration linking the overall environment.

4.2.2 Formal PMIS use and informal project communication

Throughout the interviews, PMIS was not mentioned to be the sole environment in which project work traversed. Rather, respondents made a relatively stable distinction between the formal role of PMIS and the channels of coordination where coordination frequently commenced. Documentation, visibility, records, and follow-up were the primary characteristics of PMIS, and more frequently, the first-line action was phone calls, email, and Teams or chat messages when work had to be made as fast as possible. In other cases meetings were still significant, yet the most consistent pattern was that of these expedited day-to-day routes. It implies that the project information environment is structured not just according to the fragmentation of systems, but also to a functional division between formal information structures and everyday communication channels through which work is furthered in practice.

PMIS functions mainly as a documentation and situational-awareness tool

Some of the participants explained the primary value of the existing PMIS as a project overview as opposed to the location where all activities are performed. INT01 wrote that the primary role is to provide the situational awareness in the project and INT08 said the same thing, but that PMIS is primarily used to provide follow-up, document control, and situational awareness. The same logic was articulated by INT09 in rather different terms, with project visibility being the primary role: the necessity to know status, hours, costs, files, open issues, and what had to be done. In these interviews, PMIS emerged as the official layer in which information is exposed, recorded and can be utilized in a follow-up, although it may not have full coordination in terms of practicality in that layer. This is one of the most obvious results of the material due to its repetition in various work situations and job descriptions.

Informal communication remains the first-line coordination channel

Simultaneously, the interviews revealed that the urgent coordination and routine starts out-of-formal PMIS processes. This pattern was explained in INT08: in case something is urgent, people call. In case something requires written documentation, it goes into email. In case it is a small quick question, it is Teams message. INT01 reported a comparable division with more standardised project information passing via PMIS or project tools, but with urgent matters done by phone or Teams. INT09 justified the same larger pattern with a more precautionary observation that the urgent issues still went first by phone, but minor daily issues were quickly resolved in Teams and many issues began out of PMIS and then later recorded where needed. Combined, these descriptions indicate that formal system design is less important in the selection of communication channels than is immediacy, convenience, and the pace of the situation. This was not introduced as a side-whisker, but as a work roundabout of the daily project co-ordination.

Email still provides traceability and accountability

In this broader communication scheme, email played a narrower role because it did leave a written trail that could be verified. This aspect seemed to be particularly well-illuminated by INT08, which made a direct connection between email and a set of circumstances, where a written record had to be provided. The same role was strengthened by INT01 with the help of a concrete case when additional work was discussed over the phone, and it was later doubted due to the lack of a written document: If you had an e-mail on that, you would have something written. In this regard, email served as an intermediary between expeditory practical com -communication and official responsibility. In most instances it was not part of the main PMIS workflow, yet was appreciated as it maintained a record of what was said, agreed or approved. This is one of the reasons why email still plays a unique role even in the projects where multiple digital tools and channels are used.

Scattered information creates retrieval and version confusion

Later retrieval becomes challenging when there are various channels of communication and records. INT09 was a situation where individuals were attempting to reminisce in whether a previous choice had been made in Teams, email or meeting notes, and the central issue was that it was taking too long to locate it. INT08 had a very similar version-control issue where an old PDF in an email chain needed to be verified with the new one in the document system to carry on. INT02 gave a case in point when a number of individuals in a meeting were seeking out a prior conversation and attempting to recall where the discussion was recorded. These instances imply that it is not the case that information usually fades away. Frequently, the information remains in some form, just not at the right place at the right time, or it is duplicated or just hard to reach with certainty.

PMIS is bypassed under speed and workflow pressure

Another common theme was that formal PMIS paths were even avoided as they were thought to be too sluggish or too complex to allow the working speed. It was said in INT01 as follows: In the case of need to communicate quickly, then people will go around it. INT08 presented the same practical argument, and said that it occurred when they would work out the problem first and make a note afterwards, or would create their own Excel or list be-cause the official route appeared too sluggish to perform such a trivial task. INT09 also implied prompt reactions through the phone or Teams prior to further documentation where required. A smaller consulting based case, which was the continuation of this tendency, was that of the INT05, where phone and email-based communication remained the main one. Such tales do not imply that PMIS is rejected as such. Rather, they cite the fact that bypass is often highly feasible: it is an indicator of a disjunction between the formal processes and the pace of the project in contrast to the simple resistance to digital tools.

The interviews, in general, suggest that PMIS offers a significant formal layer of project control, records, and visibility, but not in its entirety the first-line communication within which many of the project actions are initiated. The resulting information trail is thus usually parallel to each other, not fully integrated: one aspect of project reality has become formalized in PMIS, another aspect continues to be revealed first by phone, email, chat and, in some instances, by meeting before it is documented, and, in others, not at all. This information is summarized in Table 4.4, and Figure 4.2 shows the parallel information flow modeled in the interviews.

Table 4.4 Formal PMIS Use Versus Informal Project Communication in Daily Work

Channel or environment	**Main role in practice**	**Typical use case**	**Main strength**	**Main limitation for PMIS readiness**

PMIS / project platform	Documentation, follow-up, visibility, approvals, and project overview	Status tracking, document control, issue tracking, cost and hour follow-up	Structured overview of the project and its formal records	Does not fully capture the first communication round of daily coordination
Email	Written traceability and accountability	Confirming agreements, preserving proof, sending formal messages	Can be checked later and supports responsibility	Important communication may remain outside the main PMIS record
Phone	Immediate coordination	Urgent clarification, direct contact, rapid action	Fastest route for urgent matters	Weak traceability unless documented afterwards
Teams / chat	Quick everyday coordination	Small questions, updates, short clarifications	Low friction for routine communication	Harder to retrieve later if not formalised
Meetings	Shared discussion and coordination in selected topics	Reviewing schedule, issues, procurement, or cost topics	Supports collective understanding	Decisions may still be difficult to locate later if records are dispersed
Personal lists / local spreadsheets	Supplementary individual control	Own follow-up, temporary tracking, local workarounds	Flexible and easy to use quickly	Further fragments the information trail

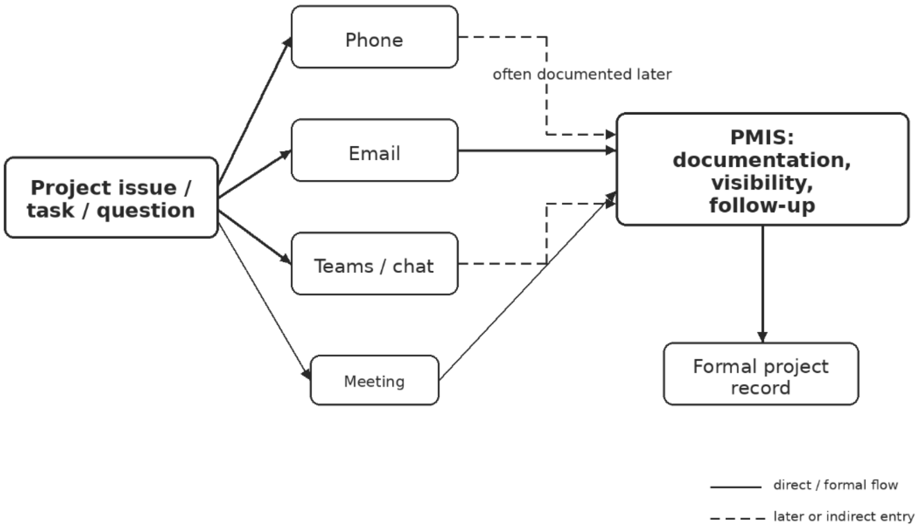

Figure 4.2 Parallel information flow between informal coordination channels and formal PMIS recording.

Figure 4.2. In the interview material, project information often moved first through phone, email, or Teams/chat, while PMIS served mainly as the environment for formal records, visibility, and follow-up; meetings remained important in some situations, but the overall information flow was parallel rather than fully contained within one system.

4.2.3 AI readiness depends first on trustworthy, structured, and governable project data

In the interviews, preparations to AI and machine learning were characterized more as an issue of data than a matter of software availability. There was no general opposition of AI by the participants. Rather, they recurrently connected beneficial AI/ML-enabled PMIS to the previous requirement that project data should be correct enough, organized enough, comprehendible enough, and controlled sufficiently to be dependable. In this regard, the interviews indicated more that no one is not interested in AI than that they do not know whether existing data on projects can be trusted and managed sufficiently to use it as a secure foundation on this matter.

Good data quality and standardisation are treated as basic prerequisites

It was also one of the most recurrent and noticeable results in the material. The useful AI was constantly pointed out by respondents that depends on clean, well-organised, and documented data that is sufficiently consistent. INT02 made it sounding: The poor quality of the data does not require the AI feature. INT08 further emphasized data quality as a solution to be addressed first, mentioning fragmented structure and recording practices as a major obstacle and pragmatically saying that AI would just accelerate bad data when it had weak foundations. The same problem was generalised by INT09, which noted that the more data is standard, the easier work is and the later AI can help. All of these reports suggest that the participants did not perceive AI as a resolution to subpar information foundations. Rather, the readiness of AI is viewed as an issue that needs to first augment those foundations.

Not all project data is trusted equally

The interviews also revealed that confidence in project data is rather uneven but not general. The category of cost data was the one that was most frequently handled as the more reliable one due to its commercial significance and hence verified more thoroughly. This was clear-cut as INT09 said that cost data is the most trusted since it is significant to business and INT08 similarly outlined cost and approved-document data as the most trusted be-cause errors most easily discovered and version control more evident. In contrast, schedule updates and progress data were reported more frequently as problematic. Several participants observed that this type of data is not always congruent with the reality of the site or can be inputted in inconsistent forms, and therefore, it is more difficult to believe without additional verification. This difference is relevant since it implies that the existing PMIS settings might already have a number of comparatively reliable data domains but not every piece of project information has the same readiness value to be used by AI/ML.

Project information continues to rely on human confirmation and contextualization

Although data were in digital form, even in these cases, participants still tended to think that it needed human verification and interpretation before it could be utilized with any confidence. INT01 expressed this more than any other, pointing out that all datasets still needed to be reassuranced somewhere or by someone that it was correct. In a different section of the same interview, he explained that he would trust the information after verifying it with the site supervisors and the truth of the site as opposed to the progress reports at face value. The added dimension with INT07 was that the data is not always the problem, but the capability to receive and interpret it properly, especially when business conditions, or system logic are viewed as incomplete knowledge by key figures that are being read. INT08 rendered the same issue more feasible by indicating that various entry practices could render the same data hard to interpret uniformly. These descriptions imply that preparedness does not only depend on the availability of data, but also on whether it can be put into context without unduly taking recourse to tacit human judgement.

Ownership, confidentiality, privacy, and governance risks remain unresolved

Another significant limitation on preparedness was data governance issues. These interviews began to cross-over into the technical data quality and focus on control, ownership, confidentiality and the ultimate destination of the data. INT01 augmented this once more and once more in a more material sense, relating the application of AI to the problems of NDA, external data sharing and ownership of the information generated as a consequence. He referred to non-owned data as a very big risk, a very big blockage to most companies and even reduced the problem further by stating that whoever desires the data owns everything. Notably, this issue was not a one interview issue. INT09 also highlighted the importance of data ownership and that businesses would prefer to know the owner of the data. Governance of the interviews in this case was not tabled as a far-off legal issue, but as a working state of a trust. Provided that the ownership, control, confidentiality and location of data are not well understood, then the participants revealed that even in the case of the technical potential, organisations will be hesitant to touch AI-ready PMIS. The smaller, but still significant trend was that data quality accountability is not the responsibility of a single position but shared by multiple positions. This was expressly stipulated in INT09, which discussed the fact that the responsibility is often split between the project manager, site, finance, procurement, design and IT. It is not such a robust subsection as the bigger problems of quality, trust, interpretation and governance, but it helps to understand why it is hard to improve: data readiness, depends on coordinated practice involving many functions, not a one technical fix.

In general, the results indicate that AI preparedness in PMIS is limited not by a deficiency of interest in AI per se as much as by the unsolved issues of data quality, trust, interpretation, and governance. The participants tended to be receptive to the helpful AI support, yet they did not consider such support to be credible unless the data underlying the project was sufficiently reliable, organized, and controlled. These conditions are summarised in Table 4.5.

Table 4.5 Data Quality, Trust, Governance, and AI Readiness Conditions

Data readiness condition	**Stronger current position / more dependable side**	**Weaker current position / key risk**	**AI/ML readiness implication**
Data quality and standardisation	Data that is structured, consistently recorded, and easier to search or compare was seen as a stronger basis for later AI use	Data spread across many systems, formats, and recording logics was seen as weak input that AI would not solve	Readiness depends first on improving data quality and standardisation before AI can be trusted to add useful value
Trust in data types	Cost data and approved documents were more often treated as dependable because they are checked more carefully	Schedule and progress data were trusted less where they diverged from site reality or were entered inconsistently	Current readiness is uneven because some data domains appear more usable for AI/ML than others

	and version control is clearer		
Interpretability of data	Data is more usable when it can be understood in context and linked clearly to business and project reality	Data that requires heavy reassurance, tacit checking, or interpretation by experienced people remains harder to use confidently	AI-ready PMIS remains limited where data is not sufficiently self-explanatory or contextually robust
Ownership, confidentiality, and governance	Clear control, permissions, and ownership were associated with safer and more acceptable future AI use	Unclear ownership, confidentiality concerns, and uncertainty about where data goes were treated as major barriers	Governance uncertainty weakens trust in AI-ready PMIS even where technical possibilities exist
Coordinated responsibility / fragmented responsibility	Better conditions exist where responsibility for data is understood and coordinated across functions	Split responsibility across project, site, finance, procurement, design, and IT makes consistent quality harder to maintain	Readiness is harder to strengthen because data quality depends on several actors rather than one clearly controlled process

4.2.4 PMIS readiness also depends on organisational routines, support, and workflow fit

The interviews also revealed that systems and data alone do not yield PMIS readiness. Readiness, even where digital tools exist, remains a matter of whether organisations deploy them in practice frequently enough, whether users become familiar with the processes they are intended to model, whether there is support, and whether the systems such as these match the reality of project work. In this regard, preparedness was manifested as a socio-technical state: technically competent instruments did not necessarily translate into the practical readiness in case the fit of routines, direction, and workflow remained unbalanced.

Formal PMIS processes may exist, but implementation is uneven

Among the most obvious organisational findings was the fact that rules, instructions or the intended manner of working were in fact present yet the manner in which they were applied varied significantly. This was characterized in INT09 itself: there were written rules and agreed courses but still, in the actual project it is people and time pressure that makes the difference and some teams adhered to the course and others cut corners. This was also reported by INT08 but slightly differently, with the observation that rules and instructions existed, however, implementation remained to be affected by people, project pressure, and client way of working. INT01 similarly explained standardised processes as broadly existing, but the actual implementation of these processes still majorly relied on the people concerned. Combined with these accounts, we can posit that organisational readiness is not as constrained primarily by the lack of process, but by the disproportionate translation of process into the daily project practice.

PMIS use varies by project, client, and organisational context.

It was also made clear by the participants that the use of PMIS is not universal among the projects. Rather, it is dynamic to client demands, project, and organisational environment. INT01 explained this using client expectations whereby some clients are satisfied with the normal practice of the company and others wish to get more or less information, so the mode of operation invariably varies according to the side of the client. This was reinforced by INT05 who added that clients usually determine what is used and then that is what the pro-project adheres to. INT06 also explained the use of tools as being completely project-wise with the end users or clients usually making decisions about what systems are needed in a particular project. This variation is important since it predisposes readiness asymmetry; PMIS utilisation is influenced by the external project environments in which organisations have to be, as well as internal organisational intent.

Training, support, and peer learning shape actual use

The other powerful trend was that PMIS capability is developed based on a combination of formal onboarding and informal peer support as opposed to formal systems only. INT09 explained that internal training and onboarding are important but noted that most individuals continue to learn through doing and peer assistance is also highly necessary. INT08 was nearly the same: onboarding, internal training, support of more experienced users, and people who are more familiar with the systems. The same model was named by INT01, where there were the right inductions, but it is still important to be supported by more knowledgeable users due to the fact that not all the things are taught or recalled during an official induction. INT02 also included internal administration users, who train. The interviews thus indicate that the real PMIS preparedness is largely dependent on support systems that are entrenched within the daily work. The formal training is important, yet peer help, experience, and understanding of processes in the field are important.

Usability and workflow fit influence adoption and bypass.

Another area that participants attributed readiness to is the simplicity of PMIS to use, whether it provides a clear direction to the user, and whether it aligns with how project work is conducted in practice. INT09 stressed the importance of a more detailed instruction that would allow users to operate more consistently and realize the reasons why the process works the way it does. The same inter-view also indicated the usefulness of systems that alert the user when missing crucial information is present before bigger downstream issues occur. INT07 provided an excellent supporting point, explaining a new ERP system that has embedded instructions and a user interface that will tell the required steps, as a way of harmonizing operations. In comparison, the older ERP was reported to provide a broad range of possible ways of working without any warnings regarding the absence or wrong inputs and so the users would learn by errors. The point made by INT01 in support of this chain of reasoning was that in the wider usability context simplification was the key direction of design. These accounts combined imply that PMIS preparedness does not solely hinge on the presence or absence of processes, but on how the system assists the user to follow the process and aids the normal workflow and the necessity to circumvent official channels.

One last, more competent fact is that capability seems to be distributed in practice unevenly. This must not weigh down the subsection as compared to the greater process, variation, training, and usability results, but nonetheless, it aids in understanding why implementation remains ambivalent. INT09 observed that site people occasionally circumvent formal procedures because they are not familiar with the processes, whereas INT01 indicated that formal procedures might not have been adequately explained to site people. INT04 provided a supportive example that the use of advanced software can be better situated in office based or specialised jobs than on the site. These should be considered as a more limited qualifier than the actual organisational argument, but they suggest that PMIS preparedness may depend not only on the role but also on the project.

These results imply that PMIS readiness is socio-technical: even technically-enabled systems fail to generate readiness unless the users, routines, support structures, and workflows are well-enough aligned in practice. Table 4.6 summarises the organisational conditions found in the interviews.

Table 4.6 Organizational Routines, Support, and Workflow Fit in PMIS Readiness

Organisational factor	**Formal or intended condition**	**Practical reality in use**	**Readiness implication**
Process and rules	Written rules, instructions, and agreed ways of	Actual implementation still varies with people, time pressure, teams, and project conditions	Readiness remains uneven when formal process does not translate

	working exist in some settings		consistently into daily practice
Project and client adaptation	Organisations aim to work through established PMIS routines	PMIS use changes across clients, projects, and organisational settings	Readiness is not uniform because companies operate in different external project environments
Training and support	Onboarding, internal training, and induction are available in several cases	Much actual learning still happens through peer help, experienced users, and learning by doing	Capability depends on everyday support structures, not only on formal training provision
Usability and workflow fit	PMIS is intended to guide work through structured processes	Systems may still feel heavy, unclear, or insufficiently guided, which encourages workaround behaviour	Readiness improves where systems are simpler, better guided, and closer to real workflow needs
Capability across roles	PMIS processes are intended to be usable across roles	Confidence and process understanding are uneven, with some roles relying more on bypass or local workarounds	Uneven capability contributes to mixed implementation and local inconsistency

4.2.5 AI is already used in project work, but mainly in limited support roles

In the interviews, AI was referred to as already evident in project work, but in a very limited and narrow sense. The participants did not model the present practice as one of a completely AI-powered project management systems. They described, instead, a situation in which AI already penetrated everyday work because of applications of pragmatic support, but implementation into PMIS had not reached any significant level. The interviews therefore did not focus on the presence of AI as much as on the existing presence of the latter in project settings.

Current practical AI use is already visible

The most evident evidence in this theme was through what people used to do on a daily basis. INT08: INT08 reported using Copilot or ChatGPT to generate summaries, first drafts, meeting notes, structuring text, and to some extent helpful with Excel or emails, whereas INT09 did so with first summaries and first drafts. Another finding made by INT07 was that AI usage in their work was as well becoming more frequent and Copilot was already in the usage. These descriptions suggest that the concept of AI is not purely hypothetical in the materials of the interviews. It already exists but is largely confined to support work that is sufficiently narrow to be accommodated by the current work without the need to reorganise PMIS itself significantly.

AI is mostly used outside integrated PMIS workflows

Although it was currently used in a visible way, it was not generally reported to be a deep embedded PMIS intelligence by the participants. This was explicitly mentioned in INT08, which mentioned that there was no yet systematized AI-driven PMIS in everyday project work, and INT02 explained the state of the art by saying that it was predominantly people or teams using LLM-based chat tools instead of project-management solutions. INT07 was a very useful qualifier, suggesting that AI was included in a few new systems, but this did not change the bigger picture. This evidence hence indicates that in most cases, AI is neighbouring PMIS as opposed to being part of it. Such difference is important because the implementation of AI in project work cannot be considered the sign of the full-fledged AI-enabled PMIS.

Expected value lies in speed, support, and routine assistance

The value of AI pragmatic, yet not transformative ones were the most common among the participants. The most apparent one was speed: faster summaries, less manual work, faster information processing, and document related and planning related tasks. INT08 was quite explicit in its attributing value to office routine work, summaries, messages, long text reading, document search, reminders and early warnings. INT09 similarly proposed the first useful area in support work and further added that the planning support might also be useful in other cases, where the INT07 did simple work of searching and analysing the entered in-formation and less manual work. Other more specialised or future-oriented examples, like procurement optimisation or prediction, were found in certain interviews, but were less commonly shared and thus are secondary to the more consistent pattern of bounded support value.

Human judgement remains necessary

Where AI was regarded as helpful, respondents were always able to frame it as a kind of help and not an independent choice. INT09 articulated this point in particular well when pointing out that AI provides a good start, but not a complete solution, and INT01 contended that AI ought to be assisting users, as opposed to making decisions on their behalf when it is not clear whether the facts are true. INT07 also handled AI as an instrument the outcome of which still had to be interpreted, and INT08 observed that hu-man checking was still required as the result might be too general or partially incorrect. It was a cross-interview pattern in the theme that was most stable. Participants were most ready to accept AI when it augmented work in the first stage, but they never said it was substituting interpretation, validation, or ultimate responsibility.

Trust increases in controlled environments, while overconfident AI creates concern

The question of trust in AI was not only determined on its utility, but the place of the AI and its seeming trustworthiness regarding the results. INT08 was directly linked to trust and transparent permissions, transparent responsibility, and safe environment and made known the reality that users would distrust AI, unless they knew where their data is sent. INT01 denoted controlled environments and locally controlled data centers to be the more acceptable case and INT02 also meant that in-house AI would be relatively safe. Concurrently, there were those interviewees who cautioned that even the excessively general, partly incorrect, or even unfinished results of AI would be persuasive. INT08 told us that answers could be highly confident where not reliable, and the same was told us by INT09, who said that the answer could be confident, even where not completely correct. This is this conflux of low utility and low credibility of which the subsection is worried. The reason why the participants did not oppose AI was that it was new; when it was under control, of course, under government, of course, under human check-ing, they were the most accepting of it.

The combination of the findings indicates that AI is already involved in project work, albeit primarily as limited support, as opposed to complete PMIS intelligence. It is currently mostly used in the summaries, drafting, search, reminders etc. routine support functions. The greatest perceived value is perceived time and manual effort reduction most and the perceived limits are the overconfident output, uncertainty of trust and yet necessity of human judgement. These patterns are brought together in Table 4.7.

Table 4.7 Current AI Use, Expected Value, and Bounded Role in Project Work

AI-related pattern	Current use / expectation	Perceived value	Limitation / concern	Readiness implication
Current practical AI use	AI is already used in summaries, first drafts, meeting notes, search, and other support tasks	Practical benefit is already visible in everyday office work	Use remains narrow and task-specific	AI is present in practice, but mainly in limited support roles
AI and PMIS integration	AI use is still often individual, team-level, or tool-specific rather than deeply embedded across PMIS	Users can experiment without large system change	Integrated AI-driven PMIS remains uncommon	Current readiness is stronger for adjacent tools than for fully integrated AI-enabled PMIS

Expected value of AI	Main expected value lies in speed, support, routine help, and selected planning or document-related assistance	Less manual work, faster summaries, better search, quicker support for routine tasks	More specialised prediction or optimisation uses remain narrower and less consistently supported	Readiness appears stronger for bounded support functions than for advanced autonomous use
Human judgement and bounded role	AI is seen as useful for first drafts, suggestions, and support, but not as a final decision-maker	AI can improve first-stage work and reduce effort	Output still requires checking, interpretation, and human responsibility	Current readiness is compatible with assistive AI, not with replacing human judgement
Trust conditions and perceived limits	Trust is stronger in controlled and clearly governed environments	Acceptance increases when permissions, responsibility, and data handling are clear	Overconfident or partly wrong answers weaken trust, especially when users cannot verify them easily	Trust remains conditional and limits wider AI uptake in PMIS use

4.3 Cross-theme synthesis: current readiness profile of PMIS in Finnish construction

In other words, the five themes of the interview spell out a not-so-strong-and-not-so-weak readiness profile. The findings show that digital, formal PMIS functions, and sparse

AI utilization is already a reality within the Finnish construction practice, but they also prove that the overall requirements of a trusted AI/ML-based PMIS are still skewed. The following part, therefore, tries to put the above inferences in or-der to find the key enabling conditions, the key cumulative constraints and the overall empirical readiness profile that emerges out of the interview material

4.3.1 Main readiness enablers

The contents of the interview suggest that there are already certain key enabling conditions. The construction projects in Finland are not beginning with a clean slate: the players outlined current PMIS platforms, document systems, reporting tools, ERP-linked information, and in a few instances, BIM or IFC utilization as existing project set-ups, although these were fragmented or in some instances, only partially interconnected. Stable formal role in visibility, records, documentation and follow up already exists in PMIS, which implies that some formal practice of information is already in place. Moreover, the interviews revealed that practitioners were interested in limited AI support, in particular, in situations where AI could save time, minimize routine activities, and help with summaries, search, drafting, and the like. It also has some rules, onboarding practices, training arrangements, and peer-support structures, which are already present organisationally. It is not that these enabling conditions are high readiness in themselves, but they do imply that the environment already has a partial base on which a higher level of AI/ML-enabled PMIS capability could be built.

4.3.2 Main readiness constraints

Simultaneously, the results indicate that there are a number of cumulative limitations on existing preparedness. The technical base is still undermined with broken system landscapes, unfinished integrations, redundancy of entry, file exports, and manual transfer. The presence of PMIS is also accompanied by a parallel pattern of communication whereby urgent and routine coordination may tend to start outside the system, indicating that formal records of PMIS may not reflect the actual flow of information of project work. The limitations of data are still at the centre stage: mistrust towards various types of data exists, no complete standardisation has been made, it has to be human verified and the questions of ownership, confidentiality, and control of data have not been answered yet. The organisational capability is also disproportionate since there might be rules, but they may be applied differently in each (project, client, team, role) and training, usability, and workflow fit are not consistent. Lastly, the existing AI application, as it is already evident, is limited and has not yet penetrated PMIS to a profound extent. These limitations when combined imply that the present limitations are not the result of a single missing technology, but the frailty of the broader socio-technical base of PMIS use

4.3.3 Overall empirical assessment of current PMIS readiness for AI/ML

In general, the results indicate that the existing PMIS in Finnish construction does not presuppose the complete preparedness to apply AI/ML but a biased preparedness. This data indicates that support functions prove to be more prepared than inde-pendent intelligence. The respondents clarified the existing digital tools, built documentation and follow-up policies, and the growing tolerance towards the lim-ited artificial intelligence support, especially in the summaries, reminders, search, drafting, or other more prosaic support operations. In this aspect, the current environment is to a certain extent already prepared with the foundation of a practical AI application.

Simultaneously, the findings imply that the readiness is limited more by the underlying basis rather than the uninterestedness. The overall distrust towards AI is not reflected in the interview topic. Rather, it cites disorganised systems, piece-meal flows of information, differently bestowed trust, unresolved governance issues, and unequal organisational capacity as the primary factors that make sure that wider AI/ML-enabled PMIS application is kept to a minimum. This implies that the existing barrier will not be on the concept of AI but on the willingness of the imminent PMIS surrounding to implement it in a reliable fashion.

The overall profile can then be defined as developmental, rather than mature. Digital tools already exist on-the-job, and AI applications already exist and practitioner interest in bounded support functions are evident. However, the larger PMIS ecosystem is not fully integrated, standardised, trusted, and governed to support more sophisticated AI-enabled PMIS applications at scale. Overall, the findings suggest that in Finnish construction, PMIS is now more or less prepared to be combined with AI/ML that promise in the chosen sup-port applications, but not sufficiently prepared, standardised, trusted, and gov-erned to be utilized as an AI-enabled PMIS on a broader scale. In Table 4.8, these cross-theme patterns are summarised.

Table 4.8 Cross-Theme Synthesis of Current PMIS Readiness for AI/ML in Finnish Construction

Cross-theme dimension	Main enabling conditions	Main constraints	Overall readiness implication
Technical and information-system foundation	Digital platforms, document systems, reporting tools, and other project information tools are already present in practice	Fragmented system landscapes, incomplete integration, and repeated manual transfer weaken coherence	The technical base exists, but it remains too uneven for stronger integrated AI/ML use
Data trust and governance	Some data domains and formal records are already relatively dependable	Uneven trust across data types, limited standardisation, continued need for human verification, and unresolved ownership or control questions remain major barriers	Readiness is constrained unless project data becomes more trustworthy, structured, and governable
Organisational routines and workflow fit	Some rules, training practices, and support structures are already in place	Implementation is uneven across projects, clients, teams, and roles; usability and workflow fit remain inconsistent	Organisational readiness exists in part, but it is not yet stable enough across practice

Current AI use and AI role	AI is already visible in bounded support tasks and has clear practical value in selected areas	Use remains limited, weakly integrated into PMIS, and dependent on human checking and controlled trust conditions	Current readiness is stronger for assistive support functions than for broader AI-enabled PMIS integration

4.4 Comparison of Manual NVivo Coding and Copilot-Assisted Coding

To check this as a comparative analytical control, NVivo coding was done manually and compared with a Copilot-assisted NVivo coding of the same material of the interview. The aim of the comparison was not to compare the two approaches as one and the same method, but to evaluate to what degree they yielded similar thematic patterns and areas in which they differed in emphasis or structure influenced interpretation. In general, there is a high degree of substantive convergence, as revealed by the comparison. Both methods single out the same overarching challenges defining PMIS preparedness in Finnish construction such as fractured system environments, formal use of PMIS and informal communication coexisting, and uneven data quality and trust, manual work persisting, unequal user ability, and reservations about AI. Meanwhile, thematic granularity and definition of boundaries are different between the two approaches. The structure generated by the manual analysis is more differentiated and context-sensitive, and the Copilot-assisted coding will be more inclined to generalize similar issues into overarching thematic categories.

4.4.1 Comparison of thematic structure

The most apparent area of intersection is the general organization of the findings. Both approaches recognise fragmentation, non-formal PMIS communication, uneven data trust, manual duplication, uneven organisational capacity, and wary AI anticipation as the key concerns that define PMIS readiness. This consistency is important in the sense that it provides an indication that the primary findings are not reliant on a single route of analysis. Although the thematic labels vary even in the case where they vary, the same empirical pattern is re-emerging in both analyses.

The key divergences are about thematic resolution as opposed to contradiction. NVivo analysis manual differentiates better structural conditions, behaviours-practices, data-related issues, and organisational conditions. It is particularly apparent in the coverage of PMIS use and communication, where the manual analysis differentiates the documentation and control aspect of PMIS and the everyday practicality of going around it in day-to-day coordination. An analogous distinction is evident in the organisational theme, where the manual analysis shows to be a better measure of workflow fit, process discipline, and client variation, compared to the smaller Copilot-assisted theme on training and user adoption.

A similar trend is developed in the AI-related content. Both reviews are pleased that AI already exists in the project work, although in the sphere of limited sup-support and under suspicion. Nevertheless, the analysis based on manual is more discrete in separating the present practical usage, the limited value of support, the present requirement of hu-man judgement, and the conditions, when AI is considered to be reliable. A substantive conclusion, though made with the help of the Copilot, is also similar, but it brings together these points and makes them more general and more holistic AI theme. Together with one other, the comparison suggests that the main difference between the two methods is the analytical granularity: the manual analysis is more differentiated, and the Copilot-assisted analysis is more compact and synthetic.

Table 4.9 Comparison of Manual NVivo Coding and Copilot-Assisted Thematic Coding

Manual NVivo theme	Copilot-assisted theme	Main correspondence	Key difference

Current PMIS is fragmented, weakly integrated, and manually connected	Fragmented system landscape and missing integrations	Strong direct correspondence	The manual analysis gives more operational detail on weak integration, transfer failure, and the system landscape as a structural condition
PMIS mainly supports documentation and control, while daily work starts outside the system	Communication practices that bypass PMIS	Strong substantive correspondence	The manual analysis distinguishes more clearly between the formal role of PMIS and the bypass of PMIS in daily coordination
AI readiness depends first on trustworthy, structured, and governable project data	Data quality, trust, and ownership	Strong direct correspondence	The manual analysis places stronger emphasis on governance, standardisation, and interpretive control, while the Copilot-assisted version is more compressed
Manual transfer, duplication, and inefficient workflows	Manual work, duplication, and inefficient workflows	Strong direct correspondence	The Copilot-assisted coding treats this more explicitly as a standalone theme, whereas the manual analysis links it more tightly to fragmentation and integration weaknesses
PMIS readiness also depends on organisational routines, support, and workflow fit	Training, support, and uneven user adoption	Partial but substantial correspondence	The manual analysis includes process discipline, usability, workflow fit, and client variation more explicitly, while the Copilot-assisted theme is narrower
AI is already used in project work,	AI expectations, early	Strong thematic overlap	The manual analysis separates current practical use, bounded value, human judgement, and

but mainly in limited support roles	pilots, and guarded trust		trust conditions more clearly, while the Copilot-assisted coding integrates them into one broader AI-related theme

4.4.2 Comparative analytical assessment

The comparison provides the credibility of the results in a sceptical yet constructive manner. The substantive overlap of the two approaches is strong, which implies that the findings of the two thematic conclusions are based on the recurrence patterns of the interview material rather than a single reading of the data. Meanwhile, the divergences indicate that interpretive judgement is also significant, specifically when it comes to establishing thematic boundaries and maintaining context-dependent differences. In this sense, the manual NVivo analysis will be the main analytical framework of the study, as it is more precise, contextual and delineates issues that are interrelated. The Copilot-assisted coding proves to be most helpful as a second comparative exercise that helps to verify the consistency of the key patterns and also demonstrates how the thematic synthesis can shift the focus when it is made more compressive. Combined, the two methods assist in a consistent reading of the results, which is both sound in its content, yet just wary in its interpretation.

5 Discussion and Conclusions

The chapter explains the study findings as they are interpreted with regards to the previously developed literature-based dimensions of readiness. It aims to go beyond the descriptive discussion of Chapter 4 and to discuss what the results point to regarding the AI and machine-learning preparedness of project management information systems in Finnish construction. By doing so, the chapter also reflects the implications of the study on theory and practice and ponders on the ways the findings can be used in informing knowledge in similar project settings that are not limited by the cases studied in this chapter.

5.1 Introduction to the discussion

The discussion is structured based on the general readiness profile that has been generated as a result of the study, and the key conditions that seem to define it. The literature review conceptualised AI/ML preparedness of PMIS as a multi-dimensional state of organisational setting and integration and alignment of workflow, technical and integration capacity, project and document data preparedness, governance and trust arrangements, and alignment with project and PMIS-related project success. The empirical findings can thus not be inter-deciphered as distinct themes, but as interwoven manifestations of these grander dimensions of readiness.

This discussion will start with the reflection on the overall readiness profile of PMIS in Finnish construction. It subsequently looks at the technical, data-related, governance-related, organisational and the workflow-related conditions that inform that profile and then moves to the current role of AI in project work. The theoretical and practical implications of the findings are then discussed in the chapter. Throughout, the focus is on interpretation as opposed to reporting. It is hoped to explain what the results imply, how they will be connected to the previous studies, and where their more general applicability will be more effective or restrictive.

5.2 Discussion of the main findings

5.2.1 Current readiness profile of PMIS in Finnish construction

The main finding of this thesis is that PMIS in Finnish construction seems to be partially and unevenly prepared toward AI and machine learning but not fully prepared or completely unprepared. This general conclusion is important since it shuns two naiveties that the results do not substantiate. The contents of the interview do not represent a scenario in which there are no digital tools, formal systems, and curiosity about AI. Meanwhile, it does not present a fully-fledged PMIS environment, which is already well-integrated, standardised, trusted, and governed to enable more comprehensive AI-enabled utilisation. A more precise understanding is that there are already underlying foundations, but these are not uniform in strength and are not yet sufficiently connected to rely on to enable more extensive AI/ML-enabled PMIS capabilities.

This general picture confirms the multi-dimensional concept of readiness formed in the literature review and indicates that, in construction settings, readiness is not as much determined by the very existence of digital tools as the correspondence between system integration, data state, governance policies and work-practices. Previous research had already indicated in that direction, considering PMIS as socio-technical systems and stating that the implementation of AI in the construction industry is determined by technological, organisational, and human capabilities more than it is by technical feasibility. The current results affirm that role, but also narrow it down by demonstrating the interaction of these dimensions in day-to-day project contexts where documentation, coordination, interpretation, and control are shared among a variety of tools and actors.

The outcomes also diminish more optimistic expectations regarding the feasible closeness of AI-ready PMIS. The literature review in Chapter 2 has shown that the use of AI in the construction industry is spreading, but it is very specific and not well-investigated with the mainstream project informational systems. The interview outcomes mostly confirm that trend. They state the growing application of restricted AI support yet not firmly and sure AI-enhanced PMIS. Less grandiose forms of assistive capabilities like summaries, drafting, search and selected planning support are superior in comparison with more mundane forms of integrated project intelligence.

5.2.2 Technical, data, and governance conditions of readiness

Findings indicate that technical fragmentation, data circumstances, and governance are to be seen as interconnected issues, rather than independent issues of preparedness. The PMIS in the construction industry was already predetermined in the existing literature as patchwork environments that were already impacted by the absence of interoperability, entries redundancy, and remained relying on informal tools and spreadsheets. That point of view is a powerful testimony of the text of the interview. It also extrapolates it by showing that fragmentation is not only a problem of efficiency, but a structural limitation to what future AI/ML functionality can reasonably rely on. Until the data is centrally stored in a few tools, loose-coupled reporting layers, exports and manually maintained files the digital pillars of the dependable AI use are weak.

The other point that has been highlighted by the results is that the system fragmentation is very much associated with the information-flow fragmentation. Project coordination, specific to a given project, can typically begin on the phone, through email, Teams, or in meetings, before it is documented, and may or may not be documented. This suggests that PMIS within these contexts are biased records, and not a full representation of project reality, and this places an organizational limit to the kind of AI-enabled interpretation that they can realistically sustain. This is not as straightforward as lack of interoperability of tools. It also addresses the issue of whether formal PMIS environments are capable of capturing enough actual work in project to be utilized in later analysis, retrieval, and decision support. In that regard, the study extends the previous research that has concentrated more on technical integration in that it has shown that the separation of formal and informal flow of information is also a major readiness issue.

These findings concerning data support the same conclusion. The literature review highlighted that AI usage in construction is limited by the level of data availability, the quality of data, and poorly standardised processes, and the data in the interview corroborates that trend greatly. The participants were repeatedly associating useful AI with accurate, structured and standardised project data and also demonstrated that trust differs among types of data and that data usually still needs human verification and contextual interpretation. Prior works on BIM, structured data, and document-centric AI had proposed data readiness as not just being determined by the quality of data collection, but by standardisation, connection, metadata, and usability as well. The current research confirms that perspective, however, it also includes that trust towards project data is socially differentiated: certain data is trusted, as it is commercially sensitive and it is under thorough scrutiny, whereas other data is approached with a grain of salt, since it is more vulnerable to local variation, interpretation or delay.

The same must be done with governance: this should not be regarded as a peripheral layer which is only introduced into the process after the technical preparation has been established, but as part of the preparation. Chapter 2 was a literature review that hypothesized that credible AI in construction is based on transparency, explainable, and data governance, accountability, and lifecycle-constrained safeguards. The results of the interview support that argument per se. Respondents raised issues of ownership, location of data, confidentiality, permissions, and ownership of AI-enhanced output that as of now, the willingness to use AI-enhanced PMIS is not only predetermined by the quality of data but also by the transparency of organisational control over data and models to be trustworthy. This qualifies more limited understandings of preparedness that put governance post deployment. The issue of governance is not the post-factum in the present study, but one of the aspects that determine a realistic preparedness at the very first.

5.2.3 Organisational and workflow conditions of readiness

It is also revealed in the findings that organisational routines and workflow fit underlie the AI/ML preparedness of PMIS to a high degree. Previous studies on organisational preparedness and socio-technical systems had postulated that effective AI adoption requires technological, organisational, and human capabilities, and supportive routines and culture. The current results substantiate that argument, which is further made concrete by demonstrating how formal rules, written procedures, and premeditated manners of working do not necessarily yield readiness in actual practice. Rather, preparedness is pegged on the consistency of the application of such processes across projects, teams, clients, and roles to enable consistent PMIS utilization.

This especially manifests in the difference in PMIS application in settings. According to the contents of the interview, the use of PMIS is influenced by the size of the project, client needs, organisational environment and role-specific ability. That result builds on the literature in that it demonstrates the impossibility of understanding readiness solely at the level of organisation-wide digital ambition. The applicable unit of preparedness in project settings tends to be less global, and conditional. A system can be officially present within the organisation, but the practice can be quite uneven as the conditions of projects, client needs, and local habits vary significantly to create highly disparate digital practices. It is on this account that workflow variation must be considered as a focal element of preparedness, but not as the peripheral music of preparedness.

This interpretation is supported by training, support and ease of use. The literature review connected AI/ML preparedness to change management, AI literacy, training, and favourable organisational culture. The results of the interview confirm that view in general. Participants mentioned the onboarding, peer support, internal guidance, and practical learning as significant conditions of improved PMIS usage, yet they also demonstrated that these arrangements are not even. More to the point, the results show that the workflow fit is a condition of mediation between formal system design and its real use. In areas where systems were perceived as challenging, slow, or out of step with the daily work, the tendency of users was to use informal coordination or local workarounds. This implies that preparedness is not only determined by the presence or absence of support, but by the usability of the sys-system, to such an extent that such support has any practical significance.

The consequences are socio-technical in nature. Even systems which are technically competent are unlikely to generate reliable preparedness when they fail to conform to the pace, tasks, and communication patterns of project work. Previous socio-technical literature had already proposed that PMIS should be conceptualized as interdependent assemblage of tools, roles, data structures, and processes. The current results confirm that argument and add that workflow fit is one of the points where the elements either stick together or start to drift in practice.

5.2.4 The current role of AI in project work

The findings indicate that AI is already being used in project work but to a more limited extent in support functions. The applications that were described by the participants such as summaries, drafting, re-minders, search, and selected planning or document-related support were described but none of them described a situation when AI is highly integrated into the overall PMIS environment. The difference is important as it means that the assistive use of AI is already accepted in certain aspects of project work, whereas a more integrated AI-enhanced PMIS is still far behind. The findings then show that there is a gradual adoption process as opposed to a certain level of non-use and complete use.

To a great extent, this validates previous literature, which characterized AI applications in the construction industry as being focused on individual tasks, and frequently not being strongly linked to daily project information systems. Nevertheless, the current results are also an addition to that literature in that they provide a better explanation of why this happens at the practitioner-level. Limited use seems to be more tolerable when there is a lack of continuity in the systems, imbalanced data trust, unresolved governance, and unsteady workflow fit. That is, the current role of AI is still not independent of the PMIS readiness; it is merely one of its manifestations. The first place of adoption of AI is where it can offer useful help without relying on a coherent information infrastructure.

Human judgement is still central to the role in this pattern. It was already proposed in the literature on trust, transparency and collaboration between humans and AI that AI within pro-project settings would be more acceptable when it is possible to interpret, query, and contextualize its outputs instead of passively accepting opaque recommendations. The findings of the interview corroborate that opinion. Subjects were most open to AI when it was seen as a helper to early work, but not when it seemed that it was taking over judgement in the context or end accountability. It implies that the limitation of the existing AI utilization cannot be interpreted as merely technological immaturity. It is also an indication of a logical adjustment to the circumstances where project knowledge is decentralized, local, and to some extent tacit.

The same conclusion is supported by trust conditions. When AI was explained as working in well-regulated and disciplined conditions, participants were more willing to embrace it and when the output seemed to be overconfident, weakly verifiable, or be based on data flows, whose ownership and location were unclear. Previous studies had attributed reliability, explainability, privacy, and governance to AI adoption in construction. The current research findings affirm that the concerns are relevant yet provide a better understanding that they not only influence the formal adoption decisions but also the role of AI in project work that can be accepted as acceptable. This is why the results indicate that assistive support functions that are controlled by humans are more likely to develop PMIS in the near term than general types of integrated AI intelligence.

5.3 Implications for theory and practice

5.3.1 Theoretical implications

This research provides three theoretical implications to PMIS and AI/ML readiness research. First, it reinforces and enhances the multi-dimensional and socio-technical conception of readiness that is formed in the literature. Previous studies had already indicated that the use of AI in the construction industry relies on the technical, organisational, human and governance-related factors. The current paper affirms that position, but demonstrates in more detail how these conditions work in the case when the object of analysis is the PMIS environment itself. Readiness, in this sense, cannot be defined as a feature of software per se. Instead, it arises out of the interaction between disaggregated tools, data structures, governance arrangements, routines, and real work practices.

Second, the research recommends that the information-flow fragmentation must be addressed as a part of PMIS preparedness and should be just as much as system fragmentation. Past studies had highlighted the lack of interoperability, disintegrated systems, and silo data to be major obstacles to the further application of AI in the construction sector. The current results affirm that perspective, however, also reveal that preparedness is constrained not merely by what systems do not interchange with each other, but also by the fact that significant project coordination is frequently initiated beyond the context of formal PMIS. This makes current research on PMIS refined by demonstrating that the distance between formal repositories and actual practice of coordination is not marginal. At the heart of the explanation of why PMIS can be incomplete reflections of project reality despite the widespread use of digital tools is the reason why it may be so even in situations where the latter are adopted extensively.

Third, the results indicate that AI preparedness in construction PMIS is staged. Previous literature had characterized AI applications in construction as task-specific, experimental or loosely coupled with enterprise and project platforms. The current research confirms the affirmation of the broad pattern yet introduces the limitation of the pattern to constrained assistive application that is acceptable in the nearer future as compared to profoundly integrated AI intelligence. This simulated perspective streamlines the discussions of AI/ML preparedness by separating local support functions preparedness and readiness of more comprehensive PMIS-integrated intelligence. Although the study is not a pro-positional study of a new formal theory of AI/ML readiness, it nonetheless narrows the current readiness decussations by demonstrating their functionality within the fractured and workflow-based setting of construction PMIS.

5.3.2 Practical implications for Finnish construction PMIS development

The outcomes would show to practice that the AI/ML-ready PMIS development in Finnish construction is more likely to be successful when launched on the path of improving the pre-conditioning PMIS environment and not the ambitious project of building the autonomous intelligence. A partial base is already offered by the existing digital tools, reporting views, document systems, and formal PMIS functions. However, disjointed tools capes, lacklustre integration, manual flipping and bifurcated streams of information continue to undermine how much that base can facilitate more complex functionality. The practical suggestion is that system coherence is a priority area of development, not just to facilitate efficiency but also capability of the future related to AI.

The results also point to the fact that data trust and governance are to be considered practice-ready states instead of secondary compliance challenges. Participants were also more ready to embrace AI-supported functionality where the data handling, ownership, permissions, and responsibility were more transparent, and more hesitant where they were not. It may indicate that closer consideration of standardisation, traceability, validation, and clarity of governance may support the development of PMIS and the introduction of AI/ML into Finnish construction. The study fails to find a single organisational model of doing so, although it indicates that the practical trust in AI-based PMIS depends on the perceived trustworthiness of the surrounding data environment and its perceived adequacy of control.

Another implication relates to workflows and capability of the user. The findings indicate that the development of PMIS is not likely to succeed based on software acquisition only where systems continue to be ill-matched with the speed, communication patterns and responsibility structures of the project work. Training, onboarding, peer assisting, workflow guidance, and usability are important since they determine whether formal system use is viable enough to decrease bypass. Practically, this implies that organisations that are creating PMIS to be used in AI/ML-related applications might need to consider readiness as a matter of enacted routine, rather than available technology.

Lastly, the results indicate that the most realistic next-term value of AI in Finnish construction is limited support functions. The respondents were already receptive to AI in areas where it could save time, decrease manual efforts, or support regular information processes that were controlled by people. This suggests that the wider application of AI will become tolerable initially in blatantly helpful support functions as opposed to more ambitious types of built-in AI-based project appraisal. To practice, the research therefore indicates a gradual process of growth where the limited use of support can proliferate sooner, whereas broader application is subject to more robust incorporation, more credible data, more understandable administration, and more workflow compatibility.

5.4 Limitations of the study

This work of study can be understood against the backdrop of a number of limitations. To begin with, the empirical segment of the thesis is placed in the Finnish construction and was structured to deliver a contextualised perception of PMIS preparedness in that context. The paper thus provides a view of a particular national and industry setting, as opposed to a picture of AI/ML-ready PMIS in other project-based sectors or construction settings that are more general. It will probably be most transferable to the similar project environments where the fragmented tool landscape, the combination of formal and informal information flows, and the growing interest in digitalisation and AI can be found.

Second, the qualitative interview sample is focused on empirical findings. The interviews were not intended to create statistical representation but were based on informed practitioner opinion and the group of people interviewed was primarily project managers, planners, and other professionals with experience of using digital pro-project tools in Finnish construction. This provided the study with practical richness, though it also implies that the results are indicative of a constrained spectrum of professional perspectives and cannot be construed to imply that it represents all the actors within the Finnish construction ecosystem in equal measure.

Third, the research is heavily dependent on the interview-based perceptions of the existing PMIS usage, preparedness, and development requirements. This fitted the purpose of the research, as the thesis was to investigate the description of readiness by practitioners in practice, but it also constrains the research. Interview descriptions can tell us about the experience of systems, the interpretation of the systems, and judgments about the systems, but not alone, these descriptions can confirm the technical performance of the systems under discussion. The results thus outline the perceived read-iness and perceived development requirements as opposed to actual technical audit of PMIS capability.

Lastly, the idea of comparing manual NVivo coding to Copilot-assisted coding should be interpreted as an auxiliary check of the analysis, not an independent primary research approach. The overarching analytical power of the research lies with the qualitative thematic analysis outlined in Chapter 3, such as the iterative coding, code-book cleaning, and theme building based on the interview data. The coding comparison is helpful in the justification of interpretive stability, yet, it does not substitute the analysis that is conducted by humans on which the thesis is founded.

5.5 Suggestions for future research

These results have several implications towards future research directions. First of all, it would be desirable to conduct more empirical studies where the existence of simi-lar patterns of readiness would be studied in more organisations, types of projects, and professions. It would also be valuable to carry out comparative research with Finland and other national contexts or be-tween construction and other project-related industries, in order to get a better understanding of those aspects of PMIS readiness that are context-specific and which might be more generally common. Second, longitudinal research would come in handy. The current analysis represents a snapshot of preparedness at a single time, but PMIS set-tings, information behaviours and AI applications are changing at a very rapid rate. The time-tracking of organisations or project environments may assist in shedding light on how fragmented tools capes, ways of governance, and constrained AI practices are generated and how prepared preparedness can be more predictable as systems and practices be-come established. Third, the closer implementation of future studies can be affected through studying the introduction, testing, and usage of AI-enhanced PMIS functions within a practice. This type of work would assist in determining the most realistic types of AI under current construction conditions and what organisational and technical adjustments need to be made before more widespread AI-enabled PMIS applications become a reality.

5.6 Conclusions

This thesis was aimed at assessing both AI and machine-learning preparedness of project management information systems in Finnish construction, through a connection between a systematic literature review and an empirical interview study. Combined, the findings demonstrate that PMIS preparedness in this regard is biased and incomplete. A broad scope of digital tools, formal PMIS functionality, document systems, reporting environments, and chosen AI-supported practices are already utilized as part of Finnish construction projects. Nevertheless, these components are not yet fully integrated, standardised, trusted, and governed PMIS environment to take fuller advantage of AI/ML-enabled applications.

On the high level, the study indicates that the primary constraints in the area of readiness are cumulative, but not distinct. Disruptured system landscapes, partial integration, repeat-ed manual transfer, fractured information streams, unevenly distributed data trust, unanswered governance questions, uneven organisational routines are all limiting the pragmatic conditions in which AI/ML-enhanced PMIS might be deployed more widely. Simultaneously, the results do not lead to the conclusion of lack of preparedness. Instead, they point out that preparation is more robust in limited support functions than in more thoroughly interconnected types of AI-driven PMIS intelligence. Practically, AI has already become most acceptable in terms of assisting with summaries, drafting, search, reminders, and other routine support services that are within the control of humans.

The study consequently fulfills the overall purpose of the research by demonstrating that AI/ML readiness of PMIS in the Finnish construction should be perceived as a social-technical condition. It relies on systems and data, but it also relies on workflows, routines, governance, trust, and the congruency between actual project work and the formal digital structures. The primary finding of the thesis is that the use of PMIS in construction in Finland is shifting towards AI/ML readiness, albeit more geared towards limited assistive usage than towards wider, more integrated AI-enabled PMIS functionalities.

5.7 Artificial intelligence declaration

There was also a limited and supportive use of artificial intelligence tools in the preparation of this thesis. The NVivo coding was cross-checked with AI-assisted coding only using Microsoft Copilot in accordance with the supervisor’s instruction. It was solely comparative and supportive; it did not replace the coding process of the author, or the final analysis. Grammarly was applied to correct grammar and language only.

Neither Microsoft Copilot nor Grammarly was used as a scientific source. These are tools that were not used to generate the research findings, analysis, interpretation, and conclusion of the study on their own. The author remains fully responsible for all methodological decisions, coding decisions, interpretation of the findings, and the final written content. The author critically reviewed all AI-assisted suggestions and checked them before integrating them into the thesis

References

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Davila Delgado, J. M., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering, 44*, 103299. https://doi.org/10.1016/j.jobe.2021.103299

Adamantiadou, D. S., & Tsironis, L. (2025). Leveraging artificial intelligence in project management: A systematic review of applications, challenges, and future directions. *Computers, 14*(2), 66. https://doi.org/10.3390/computers14020066

Al Omari, R., Sweis, G., Abu-Khader, W., & Sweis, R. (2023). Barriers to the adoption of digitalization in the construction industry: Perspectives of owners, consultants, and contractors. *Construction Economics and Building, 23*(3/4), 87–106. https://doi.org/10.5130/AJCEB.v23i3/4.8636

Almeida, P. M., Fernandes, G., & Santos, J. M. R. C. A. (2025). Artificial intelligence tools for project management: A knowledge-based perspective. *Project Leadership and Society, 6*, 100196. https://doi.org/10.1016/j.plas.2025.100196

Al-Sinan, M. A., Bubshait, A. A., & Aljaroudi, Z. (2024). Generation of construction scheduling through machine learning and BIM: A blueprint. *Buildings, 14*(4), 934. https://doi.org/10.3390/buildings14040934

Bachari, M. S., Solouki, A., & Ghanbari, H. (2025). Exploring the application of artificial intelligence in project management: A systematic literature review. *Journal of Project Management, 10*(3), 451–468. https://doi.org/10.5267/j.jpm.2025.5.002

Bazen, A., Barg, F. K., & Takeshita, J. (2021). Research techniques made simple: An introduction to qualitative research. *Journal of Investigative Dermatology, 141*(2), 241–247.e1. https://doi.org/10.1016/j.jid.2020.11.029

Bento, S., Pereira, L., Gonçalves, R., Dias, Á., & Lopes da Costa, R. (2022). Artificial intelligence in project management: Systematic literature review. *International Journal of Technology Intelligence and Planning, 13*(2), 143–163. https://doi.org/10.1504/IJTIP.2022.126841

Chen, M., Martins, T. S., Zhang, L., & Dong, H. (2025). Digital transformation in project management: A systematic review and research agenda. *Systems, 13*(8), 625. https://doi.org/10.3390/systems13080625

Datta, S. D., Islam, M., Rahman Sobuz, Md. H., Ahmed, S., & Kar, M. (2024). Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review. *Heliyon, 10*(5), e26888. https://doi.org/10.1016/j.heliyon.2024.e26888

Ding, Y., Ma, J., & Luo, X. (2022). Applications of natural language processing in construction. *Automation in Construction, 136*, 104169. https://doi.org/10.1016/j.autcon.2022.104169

Drisko, J. W. (2025). Transferability and generalization in qualitative research. *Research on Social Work Practice, 35*(1), 102–110. https://doi.org/10.1177/10497315241256560

Du, S., Hou, L., Zhang, G., Tan, Y., & Mao, P. (2024). BIM and IFC data readiness for AI integration in the construction industry: A review approach. *Buildings, 14*(10), 3305. https://doi.org/10.3390/buildings14103305

Felemban, H., Sohail, M., & Ruikar, K. (2024). Exploring the readiness of organisations to adopt artificial intelligence. *Buildings, 14*(8), 2460. https://doi.org/10.3390/buildings14082460

Felicetti, A. M., Cimino, A., Mazzoleni, A., & Ammirato, S. (2024). Artificial intelligence and project management: An empirical investigation on the appropriation of generative chatbots by project managers. *Journal of Innovation & Knowledge, 9*(3), 100545. https://doi.org/10.1016/j.jik.2024.100545

Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Gunnarsdottir, H. (2023). A qualitative study on artificial intelligence and its impact on the project schedule, cost and risk management knowledge areas as presented in PMBOK®. *Applied Sciences, 13*(19), 11081. https://doi.org/10.3390/app131911081

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons, 65*(3), 329–339. https://doi.org/10.1016/j.bushor.2021.03.006

Hughes, L., Mavi, R. K., Aghajani, M., Fitzpatrick, K., Gunaratnege, S. M., Shekarabi, S. A. H., Hughes, R., Khanfar, A., Khatavakhotan, A., Mavi, N. K., Li, K., Mahmoud, M., Malik, T., Mutasa, S., Nafar, F., Yates, R., Alahmad, R., Jeon, I., & Dwivedi, Y. K. (2025). Impact of artificial intelligence on project management (PM): Multi-expert perspectives on advancing knowledge and driving innovation toward PM2030. *Journal of Innovation & Knowledge, 10*(5), 100772. https://doi.org/10.1016/j.jik.2025.100772

Jahanger, Q. K., Louis, J., Pestana, C., & Trejo, D. (2021). Potential positive impacts of digitalization of construction-phase information management for project owners. *Journal of Information Technology in Construction, 26*, 1–22. https://doi.org/10.36680/j.itcon.2021.001

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information*

Systems Engineering, 63(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Khan, A. N., Mehmood, K., & Soomro, M. A. (2024). Knowledge management-based artificial intelligence (AI) adoption in construction SMEs: The moderating role of knowledge integration. *IEEE Transactions on Engineering Management, 71*, 10874–10884. https://doi.org/10.1109/TEM.2024.3403981

Kineber, A. F., Elshaboury, N., Oke, A. E., Aliu, J., Abunada, Z., & Alhusban, M. (2024). Revolutionizing construction: A cutting-edge decision-making model for artificial intelligence implementation in sustainable building projects. *Heliyon, 10*(17), e37078. https://doi.org/10.1016/j.heliyon.2024.e37078

Lai, J., Chong, H.-Y., Qin, B., Liao, L. X., & Chao, H.-C. (2025). Applying artificial intelligence in construction management: A scoping review. *Journal of Internet Technology, 26*(1), 1–12. https://doi.org/10.70003/160792642025012601001

Lee, J., Ahn, S., Kim, D., & Kim, D. (2024). Performance comparison of retrieval-augmented generation and fine-tuned large language models for construction safety management knowledge retrieval. *Automation in Construction, 168*, 105846. https://doi.org/10.1016/j.autcon.2024.105846

Lemos, S. I. C., Ferreira, F. A. F., Zopounidis, C., Galariotis, E., & Ferreira, N. C. M. Q. F. (2025). Artificial intelligence and change management in small and medium-sized enterprises: An analysis of dynamics within adaptation initiatives. *Annals of Operations Research, 353*(1), 197–223. https://doi.org/10.1007/s10479-022-05159-4

Li, Y., Liu, Y., Zhang, J., Cao, L., & Wang, Q. (2024). Automated analysis and assignment of maintenance work orders using natural language processing. *Automation in Construction, 165*, 105501. https://doi.org/10.1016/j.autcon.2024.105501

Moon, S., Lee, G., & Chi, S. (2022). Automated system for construction specification review using natural language processing. *Advanced Engineering Informatics, 51*, 101495. https://doi.org/10.1016/j.aei.2021.101495

Monteiro, A., Varajão, J., & Santos, V. (2025). Effects of project management information systems (PMIS) on project manager's performance: The moderating role of PMO. *International Journal of Managing Projects in Business, 18*(6–7), 777–803. https://doi.org/10.1108/IJMPB-03-2025-0078

Müller, R., Locatelli, G., Holzmann, V., Nilsson, M., & Sagay, T. (2024). Artificial intelligence and project management: Empirical overview, state of the art, and guidelines for future research. *Project Management Journal, 55*(1), 9–15. https://doi.org/10.1177/87569728231225198

Nenni, M. E., De Felice, F., De Luca, C., & Forcina, A. (2025). How artificial intelligence will transform project management in the age of digitization: A systematic literature review. *Management Review Quarterly, 75*(2), 1669–1716. https://doi.org/10.1007/s11301-024-00418-z

Niederman, F. (2021). Project management: Openings for disruption from AI and advanced analytics. *Information Technology & People, 34*(6), 1570–1599. https://doi.org/10.1108/ITP-09-2020-0639

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction, 122*, 103517. https://doi.org/10.1016/j.autcon.2020.103517

Rane, N. (2023). Integrating building information modelling (BIM) and artificial intelligence (AI) for smart construction schedule, cost, quality, and safety management: Challenges and opportunities. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4616055

Rebuglio, M., Zenezini, G., Ottaviani, F. M., & De Marco, A. (2025). Project management information systems: A systematic review. *Procedia Computer Science, 256*, 1739–1747. https://doi.org/10.1016/j.procs.2025.02.313

Regona, M., Yigitcanlar, T., Hon, C. K. H., & Teo, M. (2023). Mapping two decades of AI in construction research: A scientometric analysis from the sustainability and construction phases lenses. *Buildings, 13*(9), 2346. https://doi.org/10.3390/buildings13092346

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(1), 45. https://doi.org/10.3390/joitmc8010045

Roulston, K., & Halpin, S. N. (2022). Designing qualitative research using interview data. In U. Flick (Ed.), *The SAGE handbook of qualitative research design* (2nd ed., Vol. 2, pp. 667–683). SAGE.

Saldaña, J. (2016). The coding manual for qualitative researchers (3rd ed.). Sage Publications.

Salimimoghadam, S., Ghanbaripour, A. N., Tumpa, R. J., Kamel Rahimi, A., Golmoradi, M., Rashidian, S., & Skitmore, M. (2025). The rise of artificial intelligence in project management: A systematic literature review of current opportunities, enablers, and barriers. *Buildings, 15*(7), 1130. https://doi.org/10.3390/buildings15071130

Shang, G., Low, S. P., & Lim, X. Y. V. (2023). Prospects, drivers of and barriers to artificial intelligence adoption in project management. *Built Environment Project and Asset Management, 13*(5), 629–645. https://doi.org/10.1108/BEPAM-12-2022-0195

Tian, K., Zhu, Z., Mbachu, J., Moorhead, M., & Ghanbaripour, A. (2025). Artificial intelligence in construction risk management: A decade of developments, challenges, and integration pathways. *Journal of Risk Research*, 1–33. https://doi.org/10.1080/13669877.2025.2512080

van Besouw, J., & Bond-Barnard, T. (2021). Smart project management information systems (SPMIS) for engineering projects – project performance monitoring & reporting. *International Journal of Information Systems and Project Management, 9*(1), 78-97. https://doi.org/10.12821/ijispm090104

Wu, C., Ding, W., Jin, Q., Jiang, J., Jiang, R., Xiao, Q., Liao, L., & Li, X. (2025). Retrieval augmented generation-driven information retrieval and question answering in construction management. *Advanced Engineering Informatics, 65*, 103158. https://doi.org/10.1016/j.aei.2025.103158

Wuni, I. Y. (2025). Critical success factors for implementing artificial intelligence in construction projects: A systematic review and social network analysis. *Engineering Applications of Artificial Intelligence, 156*, 111192. https://doi.org/10.1016/j.engappai.2025.111192

Yang, L., Allen, G., Zhang, Z., & Zhao, Y. (2025). Achieving on-site trustworthy AI implementation in the construction industry: A framework across the AI lifecycle. *Buildings, 15*(1), 21. https://doi.org/10.3390/buildings15010021

Zabala-Vargas, S., Jaimes-Quintanilla, M., & Jimenez-Barrera, M. H. (2023). Big data, data science, and artificial intelligence for project management in the architecture, engineering, and construction industry: A systematic review. *Buildings, 13*(12), 2944. https://doi.org/10.3390/buildings13122944

Zabin, A., González, V. A., Zou, Y., & Amor, R. (2022). Applications of machine learning to BIM: A systematic literature review. *Advanced Engineering Informatics, 51*, 101474. https://doi.org/10.1016/j.aei.2021.101474