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**A Trust-Based Framework for Explainable AI in Project Management Information Systems in
Construction Industry**

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ABSTRACT:

The adoption of Artificial intelligence (AI) in Project Management Information Systems (PMIS) has recently become more common. This trend is even more widespread in complex contexts like construction, where projects are based on huge dataset analysis. However, as AI systems become more developed, some new challenges emerge. Here, trust is a decisive factor that determines whether a project manager can follow AI recommendations. Some concerns in the area of transparency and accountability may hinder the adoption of AI-enabled PMIS. Project managers have to evaluate AI recommendations and then justify their decisions to other stakeholders. In this context, explainability is a must that supports trust. For this study, 10 project managers based in Finland and working in construction industry were interviewed. These interviews were conducted via Zoom and in person, and lasted around 40 to 60 minutes, from February to March 2026. Participants had to meet three criteria: three years of project management experience, familiarity with PMIS, and exposure to AI tools. They came from different sectors of construction industry, including infrastructure, EPCM, commercial, residential, industrial, and consulting. The goal of this study is, first, to understand how project managers gain trust when they use AI-enabled PMIS in their projects and second, to understand what the role of explainability is in building that expected trust. The study uses the logic of the Design Science Research (DSR) framework, which means it is both qualitative and design-oriented. The data were analyzed through thematic analysis in NVivo 15 based on the Stimulus-Organism-Response (SOR) theory. The results show that trust is not just about technical accuracy. Project managers trust AI recommendations when they are transparent enough and aligned with site realities. Moreover, trust is built when system has performed successfully over time. On the other hand, trust reduces when the system lacks explanation and acts as a black box, or when it ignores real site conditions. Trust also suffers when past AI recommendations were faulty, especially when the errors led to financial or schedule consequences. Another key insight is the "site reality gap". Even when an AI recommendation is analytically sound, it can be rejected if it ignores what is actually happening on site. These incidents often involve subcontractor delays, weather conditions, access problems, or stakeholder expectations. Participants emphasized that explainability should support understanding recommendations, assessing uncertainty, and justifying decisions or defending them against clients or stakeholders. Explanations need to be clear and layered, accompanied by key drivers, confidence levels, and visual formats. Based on these findings, this study provides a trust-based explainability framework with five layers: AI capability, explainability design, contextual alignment, accountability and governance, and human-AI collaboration. This framework can be used to develop AI systems that are not just smart, but understandable, defensible, and practical, especially in projects where decisions carry significant weight.

KEYWORDS: Artificial Intelligence, Explainable AI, Trust, Project Management Information Systems, Construction Industry, Thematic Analysis, Decision-Making

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Abbreviations

AI – Artificial Intelligence

PMIS – Project Management Information Systems

XAI – Explainable Artificial Intelligence

SOR – Stimulus–Organism–Response

IS – Information Systems

DSR – Design Science Research

RQ – Research Question

NVivo – Qualitative Data Analysis Software (NVivo 15)

PM – Project Manager

PMO – Project Management Office

EPCM – Engineering, Procurement, and Construction Management

1 Introduction

1.1 Background of Study

Project Management Information Systems (PMIS) have been constantly changing from simple systems that provide scheduling and documentation support to complex decision support systems. They have the capacity to impact management decisions. Contemporary PMIS are increasingly using predictive analytics and machine learning techniques. These tools help assess cost overruns, anticipate schedule delays, identify risks before they worsen, and optimize resource allocation (Elmousalami, 2020; Taboada et al., 2023). This gradual change in PMIS over time has shifted it from descriptive reporting toward prescriptive analytic tools. This has an effect on how managers make decisions. As a result, it is no longer just a simple reporting system.

Based on information systems research, the effectiveness of system has traditionally been evaluated by using criteria such as information quality, system quality, and user satisfaction (DeLone & McLean, 2003). However, as AI-enabled features become a part of PMIS, evaluation criteria can go beyond technical performance and include issues of interpretability and reliance. This means how easy the system is to understand and how much it can be trusted. AI systems provide probabilistic recommendations based on complex models, but users often cannot understand the internal logic behind them. This distinguishes them from traditional analytical tools (Hoffman et al., 2018).

The lack of transparency in these models creates a structural distrust in project environments. This is problematic because project managers are still responsible for decisions that would affect cost, safety, contractual compliance, and relationships with all the stakeholders. However, AI-supported recommendations may lack clear reasoning. This places project managers in a dilemma as they are accountable for the outcomes that they cannot fully understand. Research on trust in automation defines trust as the willingness to rely on a system when there are uncertainty and risks (Lee & See, 2004). Appropriate reliance means the right level of trust, that the user's confidence matches what the system can actually do (system capability).

Trust theory explains that trust is formed by what users believe about the ability, integrity, and benevolence of a system (Mayer et al., 1995). In the AI-enabled PMIS contexts, perceived ability refers to the accuracy of the predictions generated. Integrity refers to how transparent the results are. Benevolence means how well the system can align with project goals. Research in information systems shows that trust can play a crucial role in system adoption, particularly during first use. (McKnight et al., 2002). When AI outputs seem vague or inconsistent, trust may decline even if when the system is statistically accurate and reliable.

Behavioral research shows that people may reject algorithmic recommendations even after noticing small mistakes. This is known as algorithm aversion (Dietvorst et al., 2015). Similarly, perceptions of AI decision-making are shaped not only based on outcome quality. Transparency and fairness are also essential factors (Araujo et al., 2020). The results show that technical advancement is not sufficient to ensure managerial acceptance.

Concerns about algorithmic opacity have been addressed by the field of Explainable Artificial Intelligence (XAI). Here, the aim is to make model outputs understandable to human users. Techniques such as local interpretable model explanations have been employed to clarify which input variables influence specific predictions (Ribeiro et al., 2016). However, interpretability should be considered in a relevant context. Explanations are useful and meaningful when they support user reasoning and reinforce confidence in decision-making (Doshi-Velez & Kim, 2017).

Despite improvements in explainability tools, there is limited empirical research on how project managers can interpret AI-generated recommendations in PMIS. Additionally, little is known about what kinds of explanation can effectively help professional accountability. As a result, there is a gap in research that links AI decision support, trust, and explainability design in project-based settings.

This thesis is based on this assumption that explainability is not sufficient factor on its own to generate trust. Trust is a socio-cognitive phenomenon. This means that it is shaped by both social context and individual cognition. It is also influenced by

professional responsibility, experience, and organizational context. To integrate AI into PMIS, it is crucial to understand how explainability should be designed for project managers instead of technical experts.

1.2 Project-Based Organizations and the Evolution of AI-Enabled PMIS

In project-based organizations, workflows happen in temporary structures, teams formed to deliver unique outputs under constraints of time, cost, and scope. In such environments, logical decision-making is naturally complex. Project managers have to continuously balance challenging goals, align all stakeholders, manage contractual obligations, and navigate uncertainty. Therefore, the effectiveness of project execution would be tied to whether the information they rely on is accessible, reliable, and interpretable.

Project Management Information Systems (PMIS) were developed to respond to these informational requirements. Traditionally, PMIS helped project managers in scheduling, budgeting, documentation control, and progress reporting. In information systems literature, system success has been often measured by information quality, system reliability, and user satisfaction (DeLone & McLean, 2003). In project settings, this means timely data access, accurate reports, and transparency among stakeholders.

As projects have become larger and more complex, the role of PMIS has extended beyond documentation and tracking projects progress. Modern systems are employed increasingly by project managers to use predictive analytics and machine learning models to predict schedule delays, identify cost overruns, map out risk patterns and support predictive decision-making (Chitta et al., 2023; Taboada et al., 2023). This gradual change shows a transition from simple reporting to systems that actively support decisions. They also summarize past performance and generate recommendations for future action.

The relationships between project managers and information systems can be changed and simplified with more transparency through the integration of AI. Instead of

interpreting static reports, project managers now need to evaluate insight generated by algorithms. However, many advanced AI models function as opaque systems whose internal reasoning processes are not directly accessible to users (Hoffman et al., 2018). In fields like construction, where accountability for financial and contractual results is very important, if the project managers are not able to see how algorithmic decisions are made, it would create additional risk and uncertainty.

When decision-support systems guide the managerial decisions without providing transparent justification or explaining themselves, confidence in what they produce inevitably weakens (Araujo et al., 2020). These dynamic perspectives consider trust and explainability as fundamental factors in the evolution of AI-enabled PMIS.

1.3 The Development of Project Management Information Systems toward AI-Driven Decision Support

Project Management Information Systems (PMIS) have been significantly transformed over the past decades. The early versions of PMIS were basically systems that helped with scheduling, budgeting, and documentation control. These systems ensured standardization, procedural consistency, and reporting accuracy. At this point, the role of the system was to assist the project managers rather than provide analytical and interpretive information. Managers still had full responsibility for analytical reasoning and making decisions.

In early PMIS systems, performance was mostly measured in terms of the accuracy and reliability of the information. Another key factor was the efficiency of information reporting. Therefore, the system was more as an information infrastructure than an actor in the decision-making process (DeLone & McLean, 2003). However, over time, PMIS systems have developed into systems that provide integration among various functional domains such as cost management, procurement, risks, and portfolio management. However, even then, the "analytical interpretation" was mostly "human-driven" (Elgeddawy, 2026).

The development of predictive analytics and machine learning capabilities introduced another milestone in the evolution of PMIS. AI-based functionalities help decision-making through AI-driven analytics. These features include providing probabilistic forecasts, identifying unusual patterns, and suggesting appropriate alternative actions (Taboada et al., 2023). This development indicates a new shift in PMIS from tools that process information to systems that influence how decisions are made.

This shift fundamentally changes the human and system relationship. Research relevant to the role of trust in information systems demonstrates that the reliance of users on the system does not only depend on the accuracy of the system but also on credibility and transparency of the system (McKnight et al., 2002). When systems start suggesting decisions instead of just showing data, trust calibration should be considered a critical issue. (Lee & See, 2004).

The development of PMIS is not just as a result of technological advancement but also an increasing tendency towards the transfer of analytical power from humans to technology.

1.4 Artificial Intelligence in Project Management

Artificial Intelligence (AI) is playing a more important role than ever in the development of Project Management Information Systems. The functional role of PMIS in project governance structures is changed by the incorporation of AI. The distinction between algorithmic influence and human judgment becomes less clear when AI outputs move from informational support to decision guidance (Lee & See, 2004). This change is especially significant in project-based settings with contractual liability and professional accountability. In this environment, even when AI-generated insights guide their decisions, project managers are still in charge of financial results, safety compliance, and stakeholder coordination.

Therefore, even if algorithmic systems offer stronger analytical capabilities, their successful implementation depends on whether managers are able to defend system-

generated recommendations. This means that explainability and trust should be at the forefront of AI implementation in project management settings.

1.5 The Trust Problem in AI-Supported Decision-Making

It is commonly acknowledged that appropriate reliance on decision-support technologies requires trust. According to Lee and See (2004), trust in automation refers to users' readiness to rely on system outputs in the face of risk and uncertainty. Trust calibration is necessary for effective reliance, which means that user confidence must match the system's true capabilities. Decision quality can be lowered by both over-reliance and under-reliance.

Reliance on AI involves particularly high risks in project management settings because the consequences of errors are more significant (Sackett, 2024). Budget allocation, contractual compliance, risk mitigation, and safety performance can all be impacted by decisions made with the help of AI-supported PMIS. Even though AI systems are becoming more analytical, the project manager is still in charge of the results. Therefore, trust in this situation can affect outcomes both at organizational and professional levels.

One of the major sources of trust tension in AI-supported systems is the issue of opacity. Many machine learning models operate as complex computational structures. Their internal reasoning processes are not readily interpretable by end users (Hoffman et al., 2018). This "black box" feature makes the users less able to understand the rationale behind some certain predictions and recommendations. Studies illustrated that opacity can contribute to reduced trust in AI systems even when the systems perform quite well (Araujo et al., 2020).

Additionally, organizational trust theory further shows that trust in a system is a function of the users' perception of the system's ability, integrity, and predictability (Mayer et al., 1995). In the case of AI-assisted PMIS systems, the user perception of the system's ability is largely about the analytical competence. On the other hand, the user's perception of the system's integrity and predictability is related to transparency and consistency of

the system responses. A lack of understanding of the system reasoning mechanisms makes the user less likely to trust the system.

Based on information systems research, trust has been shown to influence both initial adoption and continued system use (Gefen et al., 2003; McKnight et al., 2002). In the context of AI systems in project environments, trust is thus not only a psychological concept but a determinant that affects the integration of information systems. The inability to interpret algorithmic recommendations may create a gap between technical capability and managerial acceptance.

This trust problem makes explainability not just a technical feature but a prerequisite for adopting AI systems in PMIS.

1.6 Explainable Artificial Intelligence as a Potential Solution

Recently, Explainable Artificial Intelligence (XAI) has been developed in response to rising concerns about the opacity of complex machine learning models. While traditional AI prioritizes only predictive accuracy, XAI tries to make algorithmic decision processes interpretable and transparent for users (Ribeiro et al., 2016). The goal is to provide explanations that assist human reasoning, evaluation, and decision-making.

Interpretability in AI can be comprehended at various levels. Global explanations try to clarify the overall logic behind machine learning models in the whole input space. On the other hand, local explanations concentrate on the reasoning behind individual predictions (Ribeiro et al., 2016). Interpretability needs to be evaluated in relation to the user's context and decision environment rather than based only on technical criteria (Doshi-Velez & Kim, 2017). An explanation that is satisfying for a data scientist may not be sufficient and meaningful for a manager responsible for decision-making. Those decisions can directly affect organizational outcomes.

Researchers further emphasized that the effectiveness of explanations should be assessed based on their ability to support mental model formation, appropriate reliance, and user satisfaction (Hoffman et al., 2018). According to this viewpoint, explainability is not equivalent to transparency alone. Explainability can be a relational concept

influenced by situational demands, cognitive frameworks, and user expectations (Leblanc & Germain, 2024).

In project management contexts, explainability has an extra feature which is accountability. Project managers have to clarify their decisions and the rationale behind them to stakeholders, clients, auditors, and regulatory agencies. Therefore, explanations need to be both understandable and defensible. Managers must be able to explain the reasoning behind AI-generated recommendations that affect risk mitigation or cost allocation strategies.

The growing body of XAI research in much of the literature is still largely technical, and researchers are concentrating on algorithmic methods rather than organizational integration (Doshi-Velez & Kim, 2017). Empirical evidence regarding how professionals in high-accountability environments interpret and evaluate explanations remains limited. In the context of AI-enabled PMIS, little is known about which types of explanation enhance trust, support justification, and facilitate calibrated reliance.

The research gap shows that explainability should not be considered only as a technical attribute. Instead, it should be understood as a socio-technical design challenge shaped based on the specific organizational contexts. In the case of AI-enabled PMIS, the usefulness of explainability depends on how well it can align with project managers' decisions, experiences, and accountability structures in projects.

1.7 Research Gap

This research will combine four academic domains:

- (1) The advancement of AI-generated decision support in Project Management Information Systems (PMIS).
- (2) Trust in automation and information systems.
- (3) Behavioral responses to AI-supported decision-making.
- (4) The development of explainable artificial intelligence methodologies.

Although each of these fields has made significant progress, their combination in project-based organizational contexts is still inadequately studied.

As mentioned previously, research on AI in project management has mostly focused on technical optimization, predictive performance, and efficiency improvements through data. The concentrations are also on performance-oriented applications in various project management areas (Taboada et al., 2023). These studies illustrate the analytical capabilities of AI-enabled Project Management Information Systems (PMIS). However, they have minimal understanding of how managers interpret and assess algorithmically generated recommendations.

The aforementioned literature on Information Systems indicates that trust can significantly affect adoption and continued use (McKnight et al., 2002; Gefen et al., 2003). However, empirical studies have failed to examine how these trust dimensions operate in AI-supported project decision contexts that are defined by contractual accountability.

Simultaneously, XAI literature has mainly concentrated on the development of algorithmic explanation methodologies, including local interpretability models (Ribeiro et al., 2016). Some researchers emphasize the significance of context-sensitive evaluation (Doshi-Velez & Kim, 2017; Hoffman et al., 2018). However, practical research is limited on how professionals in high-accountability roles interpret and apply explanations.

As a result, a theoretical and practical gap exists at the intersection of AI-enabled PMIS, trust calibration, and explainability design. Specifically, there is insufficient understanding of:

- How project managers perceive and evaluate AI-generated recommendations.
- How trust breaks down or is calibrated in AI-supported decision contexts.
- What forms of explanation effectively support accountability and managerial reliance.

This gap is specifically prominent in construction and infrastructure projects. In these sectors, decision outcomes carry financial, legal, and safety implications. To deal with this, it is important to go beyond technical models and instead look at how trust and explainability work in real project settings from the user's point of view.

This thesis addresses this necessity by employing a qualitative methodology. It examines how project managers interpret AI-supported recommendations. It also identifies

design principles that may promote trustworthy and accountable AI integration in Project Management Information Systems (PMIS).

1.8 Problem Statement

Although AI-enabled PMIS offer advanced analytical capabilities, trust and interpretability issues limit their effective use in project decision-making. Project managers work in environments characterized by contractual accountability, financial risk, and stakeholder scrutiny. When algorithmically generated recommendations lack transparent justification, managers may hesitate to rely on them despite their technical potential.

The core problem addressed in this thesis is the absence of a structured, user-centered framework that connects trust theory and explainability design within AI-enabled Project Management Information Systems. Without such a framework, AI systems may remain technically sophisticated but organizationally underutilized.

1.9 Research Aim

The aim of this study is to develop a trust-based explainability framework for AI-enabled Project Management Information Systems using the empirical insights from construction project managers in Finland. Additionally, it explores how explainability supports reliable decision-making in projects.

This framework bridges theoretical perspectives on trust and explainable AI with practical design considerations in high-accountability project environments.

1.10 Research Questions

This study illustrates how trust develops in AI-enabled PMIS and how explainability can shape trust in construction project environments. Based on the research objectives, the

Primary Research Questions are as follows:

RQ1: How do project managers perceive trustworthiness in AI-enabled PMIS?

RQ2: What role does explainability play in building trust in AI-enabled PMIS?

RQ3: What user requirements are needed for a trust-based explainability framework for AI-enabled PMIS?

Supporting Research Questions are:

- How do project managers evaluate AI-generated recommendations within PMIS?
- What trust-related factors influence reliance or resistance in AI-supported decision-making?
- How do accountability requirements shape expectations of explanation quality?
- What forms of explanation support both understanding and defensibility in project contexts?

These sub-questions are not separate research questions. They are used for better interpretation and are covered in the discussion in Chapter 5.

1.11 Research Objectives

To find the answers to research questions, this study attempts to:

- Examine project managers' perceptions of AI-supported decision-making in construction projects
- Identify trust-related barriers to AI reliance
- Analyze how explainability influences accountability and decision justification
- summarize empirical findings into a trust-based explainability framework
- Propose practical design principles for AI-enabled PMIS

1.12 Scope and Limitations

This study uses a qualitative research design that integrates a systematic literature review with semi-structured interviews. The study centers on project managers engaged in the Finnish construction industry. This setting is ideal for analyzing AI-assisted decision-making because of its significant financial, contractual, and regulatory accountability.

The research does not include technical advancement or practical validation of AI models. In simple words, it looks at how managers perceive trust, how they build trust, and

what they need in terms of explanation. As a result, the findings focus on social, cognitive, and organizational factors instead of algorithmic performance metrics.

This limitation is discussed further in Chapter 5 in detail.

1.13 Contribution of the Study

This thesis contributes to both theory and practice in the context of AI-enabled PMIS.

Theoretical Contributions:

- Integrates trust theory, automation research, and explainable AI within a PMIS context
- Extends understanding of trust calibration in high-accountability project environments
- Positions explainability as a socio-technical design construct not just a technical feature

Practical Contributions:

- Provides insights into project managers' expectations of AI systems
- Offers a structured framework for designing trustworthy AI-enabled PMIS
- Supports organizations to integrate AI into their project governance structures in a mature way.

1.14 Thesis Structure

This thesis is organized into five chapters.

Chapter 1 introduces the research context, outlines the theoretical positioning of the study, identifies the research gap, and presents the research aims and questions.

Chapter 2 provides comprehensive literature review on Project Management Information Systems, Artificial Intelligence in project environments, trust in automation, and Explainable Artificial Intelligence. This chapter creates the theoretical foundation of the study.

Chapter 3 describes the research methodology, including research design, data collection procedures, interview protocol, and thematic analysis approach. Ethical considerations and research methodological limitations are also addressed.

Chapter 4 presents the empirical findings derived from semi-structured interviews with construction project managers and analyzes these findings in relation to the theoretical framework.

Chapter 5 discusses the results, develops the proposed trust-based explainability framework, explains the theoretical and practical implications, and concludes the study by identifying limitations and suggestions for future research.

2 LITERATURE REVIEW

2.1 Introduction to the Literature Review

This chapter combines academic research relevant to the research problem: the integration of explainable artificial intelligence (XAI) into Project Management Information Systems (PMIS) and how it would affect trust, reliance on managers, and performance in organizations that work on projects.

The review has four sections.

First, it explains the foundational structure for PMIS and how success has been defined and measured in information systems research in the past. Second, it describes how PMIS is moving toward becoming smart and AI-enabled designs within the context of digital transformation. Third, it reviews research on technology acceptance, trust in automation, and user behavior to explain how managers use and trust complex decision-support systems. Finally, it brings the available research together to show how trust and explainability can connect AI capabilities to managerial decisions.

The purpose behind this chapter is to build a theoretical foundation for an explainable framework based on trust that can shape AI-enabled PMIS in high-accountability project environments, such as projects in construction industry.

2.2 Foundational Theories of PMIS Success and Information Systems Evaluation

It is first important to examine how information systems success is defined in broader literature. This can later lead to a better understanding of the evolution of Project Management Information Systems. PMIS are not separate technological artifacts. In contrast, they are tied to theoretical traditions that define how systems create value, how they are evaluated, and how they influence organizational objectives.

One of the leading frameworks in IS research is the DeLone and McLean Information Systems Success Model (Kodagoda, 2025). This model suggests six correlated

dimensions of system success. These are system quality, information quality, service quality, use, user satisfaction, and net benefits (DeLone & McLean, 2016). This model shows that technical performance cannot be considered the only factor to verify system effectiveness. Instead, system success can be shaped by both system characteristics and user perceptions.

This framework was later expanded by defining the measurement tools and focusing on the importance of adapting to specific contexts (DeLone & McLean, 2016). Their work explains that system evaluation must be in alignment with organizational objectives and stakeholder expectations. In the context of PMIS, it is necessary to measure success not only based on technical functionality but also through its impact on project performance and managerial effectiveness.

A thorough meta-analysis on the measurement of information system success has been performed that verifies the strength of the model across different domains (DeLone & McLean, 2016; Petter et al., 2013). The results demonstrate that user satisfaction and perceived usefulness play a key role as mediators between system features and organizational objectives. Some underlying factors later have been introduced which contribute to IS success. These include organizational support, training, and system design features; these factors can shape perceived quality and outcomes (Petter et al., 2013). This is also connected to AI-enabled PMIS, because explainability and trust can be considered characteristics that influence perceived usefulness and satisfaction.

Another model was introduced later, the IS-Impact Measurement Model (Gable et al., 2008). This model conceptualizes success by focusing on the difference between individual impact and organizational impact. Understanding this contrast is crucial for PMIS research. Although a system may work technically well, it can be unsuccessful in improving individual decision-making performance. Therefore, when evaluating PMIS, it is important to consider effects at the managerial level, not just overall project outcomes.

Afterwards, some empirical studies confirmed the importance of these concepts, which are based on user perceptions.

livari (2005) examined the DeLone–McLean model and found that there was a strong relationship among system quality, information quality, and user satisfaction. Some similar results reported the importance of perceived improvements in performance in terms of enterprise portals (Urbach et al., 2010). Tam and Oliveira (2016) combined the DeLone–McLean model and Task-Technology Fit theory and showed that system performance can influence individual performance when tasks are aligned well with technological capabilities.

Overall, all these empirical studies provide two important insights relevant to this thesis. First, the success of PMIS is multidimensional and mostly based on user perception. Second, system features can have an impact on the results through psychological and behavioral processes. In PMIS enabled by AI, explainability and trust are two crucial factors that can influence satisfaction, continued use, and net benefits. However, these models were designed for traditional systems and do not directly consider algorithmic opacity or explainability problems.

2.3 Defining PMIS (PMIS Functions, Structure, and Evolution)

The PMBOK® Guide (Project Management Institute, 2017) has clarified the definition of Project Management Information Systems. Within its context, it is explained that PMIS is an integration of tools and techniques that are employed to gather, integrate, and distribute project information throughout project management processes. PMIS can support scheduling, budgeting, resource management, procurement tracking, risk monitoring, and documentation control.

One of the earliest conceptual and theoretical frameworks for PMIS was introduced by Ahlemann (2009). Based on his framework, PMIS functionalities can be categorized into four categories: planning support, execution monitoring, control mechanisms, and reporting structures. This framework also emphasizes that integration among all phases in the project life cycle and stakeholders is required. PMIS works as a systematic, organized framework, not just a set of separate tools.

This basic framework was later expanded by a new concept called the “control tower” (Braglia & Frosolini, 2014), which is suitable for large organizations. In the extended

model, PMIS can work as unified coordination platforms and integrate all the information across various organizational departments and stakeholders. This perspective is highly applicable in construction and infrastructure projects. In these projects, project managers need to coordinate complex project dependencies.

One practical application study described that the success of PMIS relies strictly on customizing it based on the organization's workflow (Teixeira et al., 2016). Standard software and applications without adaptation to managerial processes would often result in failure to achieve expected outcomes. Another study emphasized the link between PMIS usage and performance improvements, specifically in construction projects (Obeidat & Aldulaimi, 2016). This improvement means tangible benefits, including cost reduction and schedule compliance in projects.

However, some limitations were recognized in available PMIS research. Kostalova, Tetreanova, and Svedik (2015) compared the outcomes of different PMIS software. They showed that there is variability in their performance, integration with organizations' workflows, and usability in different projects. This research suggests that PMIS capabilities depend on how managers can effectively use the system outputs.

Overall, all these studies together indicate that the role of PMIS has been transformed. It has changed from merely administrative support tools to an integrated decision framework. However, most traditional PMIS remain descriptive in nature. It is important to consider that the move toward intelligent systems creates new challenges related to cognition and governance in project contexts. This means that how decisions are understood and how they are governed in project environments are both affected.

2.4 From PMIS to Smart and AI-Enabled PMIS

Project Management Information Systems (PMIS) have moved toward intelligent designs gradually, rather than changing all at once. Early versions of PMIS could facilitate the control of documents, schedules, and budgets, and also provide proper reporting processes (Project Management Institute, 2017). Therefore, they were mainly descriptive, collecting past data and structuring the information for managerial decisions.

However, the idea of an intelligent PMIS existed long before the rise of artificial intelligence, usage which is very common these days. Jaafari and Manivong (1998) worked on the concept of Smart Project Management Information Systems (SPMIS). In their opinion, the system should be able to provide real-time and continuous evaluation of processes, integrated performance tracking, and flexible decision support. Their early ideas already match many features we now associate with AI systems.

Van Besouw and Bond-Barnard (2021) worked specifically on Smart PMIS in the context of engineering and construction project environments. Based on their research, advanced PMIS should integrate intelligence across project phases and stakeholders, rather than focusing only on data storage and transactional processing. Their framework specifically covered interoperability, data integration, predictive analytics, and automated reporting. It is important to consider that “smartness” is not just automation but the ability to support active decision-making by using analytical tools that are built directly into the system.

In the context of construction and engineering projects, Van Besouw and Bond-Barnard (2021) showed that Smart PMIS combine various data sources, such as scheduling systems, financial modules, risk registers, and external feeds. This structure can provide a framework for AI-driven predictions and optimizing decisions using AI. However, some challenges remain in terms of implementation. These are specifically ensuring data consistency, achieving organizational alignment, and maintaining system usability.

This evolution is consistent with digital transformation patterns which were first established by Oesterreich and Teuteberg (2016). They positioned PMIS development in Industry 4.0 settings where automation, interconnected systems, and advanced analytics are central. In another similar study by El-Omari and Moselhi (2011), the reporting process improved significantly in construction projects through the use of automated data acquisition technologies. These technologies allow real-time monitoring and reduce manual data entry efforts.

It is important to consider that computational complexity means a greater amount of work for project managers, and more complex work as well. Brynjolfsson and McAfee (2014) state that intelligent technologies could help experts in facilitating their work

rather than replace them. In terms of project management, recommendations generated by AI should be interpretable and clarify the reasoning behind them to support better managerial decisions.

A key issue has been raised, one for which there is a scarcity of research in PMIS. The issue is how systems becoming smarter affects the way project managers assess and trust what algorithms tell them (van Besouw & Bond-Barnard, 2021). The initial framework provides structure and architecture for intelligent PMIS, but it leaves questions about explainability and trust-building.

Therefore, moving toward smart and AI-enabled PMIS provides better analytics but also creates new challenges, both social and technical, in terms of clarity, accountability, and the way managers rely on the technology unanswered.

2.5 Trust, Technology Acceptance, and Reliance in Intelligent PMIS

As PMIS become more AI-driven, understanding how managers trust and rely on them is crucial. For this reason, considering the insights from information systems success theory, technology acceptance research, and trust in automation literature is advisable.

2.5.1 Trust within IS Success Theory

Based on the Information Systems Success Model introduced by DeLone and McLean (2016), the quality of the system and its provided information affect use and user satisfaction. This can determine whether the system delivers real value or net benefits. However, trust does not appear in this model as a separate factor. It is considered as a factor influencing how users perceive information credibility and system reliability.

According to another research (Petter et al., 2013), user perceptions can act as a mediator between technical features and organizational impact. For AI-enabled PMIS, explainability is defined as a critical design factor that shapes how users see the system. When systems provide probabilistic predictions and algorithms for prioritizations, the quality of the information in users' view depends on interpretability as well as accuracy.

Individual and organizational impact can be separated in the study of Gable, Sedera, and Chan (2008). They demonstrated why it is important to examine how PMIS affect project

managers. Therefore, trust is placed at the individual level, where it is assessed whether analytical expertise can be translated into better decision performance.

2.5.2 Technology Acceptance and Continuance Intention

More insights come from technology acceptance research. Perceived usefulness is seen as the main factor of adoption (Davis, 1989). This model was later extended by Venkatesh et al. (2003) through the Unified Theory of Acceptance and Use of Technology (UTAUT). This theory added social influence and facilitating conditions as factors that shape behavioral intention. In the context of project management, social influence can come from PMOs, senior management, or policies that require system usage. However, mandating the use of a system does not necessarily result in individuals' reliance. Therefore, if AI recommendations are not transparent, users are less likely to depend on them.

Another model, Expectation-Confirmation Model (ECM), looks at why people keep using a system rather than just why they adopt it (Bhattacharjee, 2001). According to this model, three key drivers can influence the continued use of the system. They include whether expectations are met, perceived usefulness, and user satisfaction. For AI-supported PMIS, confirming expectations is more complicated. Users may expect the system to save time, but if outputs are not clear or do not align with professional judgment, expectations may not be satisfied, and continued use may be affected.

It was found that individuals are more likely to continue using complex systems when real value is gained (Po-An Hsieh & Wang, 2007). As integrating AI makes systems more contemporary, explanations and reasoning are needed to avoid cognitive overload and disengagement. Overall, this study shows that perceived usefulness depends on interpretability in smart PMIS. When a system provides accurate but not transparent recommendations and predictions, it cannot keep users engaged and interested. Therefore, trust and interpretability are the main factors influencing whether users continue to use AI-enabled PMIS.

2.5.3 Trust in Automation and Trust Calibration

A more detailed explanation of reliance behavior can be extracted from trust theory. Trust in automation can be defined as the intent to rely on a system even when the outcomes are not certain (Lee & See, 2004). Trust calibration can also be introduced as optimal reliance, which is achieved when user confidence is properly aligned with system capability.

Trusting the system too much (automation bias) or too little (algorithm aversion) can both lead to less than ideal outcomes, also called suboptimal outcomes (Dietvorst et al., 2015; Parasuraman & Riley, 1997).

Based on the framework of Mayer, Davis, and Schoorman (1995), different concepts in AI-enabled PMIS can be defined as follows:

- **Ability** refers to how analytically capable the system is perceived to be.
- **Integrity** refers to the consistency and transparency of what the system delivers.
- **Benevolence** refers to the extent to which the system is aligned with project objectives.

It is found that trust strongly affects whether people intend to use a system (Gefen et al., 2003). For PMIS, this means that even advanced AI features may not be used if trust is lacking. PMIS can improve performance when managers actually engage with the system outputs (Raymond & Bergeron, 2008). Therefore, trust can help turn analytical capability into better decision quality. Trust calibration mechanisms and their particular importance in the context of high-stakes project environments will be explained in detail in Section 2.5.4.

2.5.4 Trust Calibration in High-Stakes Project Environments

Ideal human-automation interaction happens when trust is calibrated, meaning that what the system can actually do is in alignment with users' confidence (Lee & See, 2004). This has critical importance in project environments where risks, especially financial ones, and contractual liability are at stake.

It is found that people tend to reject algorithms after detecting small mistakes in their outputs, a behavioural reaction known as "algorithm aversion" (Dietvorst et al., 2015).

In construction and infrastructure projects, where prediction errors are highly visible and lead to unfavorable outcomes, this tendency can reduce trust in even reliable AI components.

Therefore, explainability in PMIS should help calibrate trust. It needs to support project managers to understand not just what the system predicts, but when the predictions might be less reliable. This is in agreement with Hoffman et al.'s (2018) claim that explanations should help users rely appropriately and notice errors. Explanations should help project managers understand:

- When the system can be trusted,
- Under what circumstances predictions may be less accurate,
- How sensitive outcomes may change with different inputs.

By providing clarification from both strengths and limitations, explainable PMIS can improve appropriate reliance, rather than blind dependence.

2.5.5 Trust as Mediating Factor

A consistent pattern can be seen across IS success theory, technology acceptance research, and automation studies:

1. Technical capability alone does not guarantee performance improvement.
2. User perceptions mediate system outcomes.
3. Trust influences both adoption and calibrated reliance.
4. Interpretability shapes trust formation.

In AI-enabled PMIS, explainability works as a foundation for trust. This trust can influence managerial reliance and performance outcomes. Therefore, trust is not an extra variable, but it is a core mediating factor in how intelligent PMIS work.

2.6 The Role of Explainable Artificial Intelligence in Decision Support Systems

Explainable Artificial Intelligence (XAI) was developed to address these issues. Most traditional models focus on accurate predictions. However, complex models like ensemble models and deep learning systems tend to be “black boxes” that are hard to see into. This means that users cannot figure out the logic behind how decisions are made.

Local Interpretable Model-agnostic Explanations (LIME) were later introduced to show that even complex models can offer understandable explanations for individual predictions (Ribeiro et al., 2016). As aforementioned, appropriate explanations need to be assessed based on whether they meet user needs, not technical criteria (Doshi-Velez & Kim, 2017). Thus, in PMIS, project managers need explanations that support professional reasoning and defend decisions to all stakeholders, including clients, auditors, and regulators.

According to Hoffman et al. (2018), explanations need to fulfil three purposes: helping users shape a mental model, enabling appropriate reliance, and spotting errors accurately. It is clear that the quality of explanations affects user reliance on AI. This point is directly connected to trust calibration mechanisms explained in Section 2.5.4 (Glikson & Woolley, 2020). In project contexts, calibrated trust is considered ideal, where risks and uncertainty are present and undeniable.

Therefore, the integration of XAI into PMIS cannot be considered only as a technical upgrade. Actually, it goes beyond technical enhancement. This clearly is a move toward a human-centered system design, where algorithmic intelligence is aligned with the way managers reason and make decisions.

2.7 PMIS, Project Governance, and Organizational Context

Arbabi et al. (2020) clearly show that PMIS are not isolated systems. They are designed, implemented, and enforced in Project Management Offices (PMOs). A significant number of PMOs utilize PMIS to standardize report formats and coordination in projects (Hobbs & Aubry, 2007). PMOs can also boost organizational performance by embedding governance and aligning projects with the strategic objectives of the organization.

The growing complexity in project contexts within organizations was illustrated by recent taxonomies of PMOs (Müller & Wang, 2024). Incorporating AI in PMIS requires ensuring transparency, reliability, and ethical oversight of intelligent systems. PMO functions were later extended to develop knowledge management infrastructure (Arbabi et al., 2020). This becomes more important as AI-enabled PMIS produces knowledge outputs that need interpretation. PMOs can enforce and standardize how project managers address

team needs, which may ensure that AI-generated recommendations receive proper attention (Hans & Mnkandla, 2023).

Another study emphasizes the critical role of project governance for strategic alignment (Musawir et al., 2017). For AI-enabled PMIS, governance should cover not just procedural compliance but also algorithmic accountability. This raises new issues in project governance relevant to data integrity, auditability, and traceability of explanations. Thus, trust in intelligent PMIS is formed based on system attributes as well as organizational context, governance mechanisms, and PMO oversight.

2.8 Smart PMIS and the Evolution Toward Intelligence

The idea of a Smart Project Management Information System (SPMIS) goes back before the recent application of AI in various fields. A system capable of integrating evaluation and monitoring in real time and adapting to support decision provision was proposed by Jaafari and Manivong (1998). The combination of information integration and analytical intelligence was anticipated in their first framework.

As mentioned earlier, these developments were part of the broader Industry 4.0 framework, where digitization and automation are reshaping organizational processes (Oesterreich & Teuteberg, 2016). In this context, PMIS shifts from static storage systems to dynamic, data-driven platforms.

Automated data collection improves progress reporting accuracy in construction projects (El Omari & Moselhi, 2011). Data volume and analytical capacity are increased by these advancements, but they also intensify the need for interpretability.

It is also argued that intelligent systems should enhance human capabilities and not replace them (Brynjolfsson & McAfee, 2014). In other words, AI should boost analytical accuracy while assuring managers' ability to decide at the end.

Therefore, this evolution should be gradual rather than a radical break. But even a gradual change can be the cause of new socio-technical concerns around transparency, control, and accountability.

2.9 Linking PMIS to Managerial Performance

Recent research on project manager performance has focused largely on competencies and governance (Ahmed & Lodhi, 2021; Alvarenga et al., 2019). However, we also need to consider the role of technological enablers.

Managerial efficiency and project success can be improved through PMIS (Raymond & Bergeron, 2008). Caniëls and Bakens (2012) later added that decision quality in multi-project settings can be boosted by better integration of information.

Furthermore, PMIS use is linked to individual performance outcomes. Perceived usefulness and system quality are among the factors that influence this link (Monteiro et al., 2025). As a result, system value is obtained through user engagement, not just technical advancement alone.

Performance outcomes also depend on how well managers interpret and integrate AI recommendations into their professional judgment through AI usage. In this context, explainability affects how these recommendations are understood and used in practice.

2.10 Theoretical Integration: Stimulus–Organism–Response Perspective

To synthesize the literature reviewed, the Stimulus–Organism–Response (SOR) framework is used to provide a strong theoretical foundation (Bagozzi, 1986; Jacoby, 2002). This framework, rooted in environmental psychology, explains that environmental stimuli have a strong impact on internal organismic states. These states then lead to behavioral responses.

In this framework:

- **Stimulus (S)** is defined as external environmental factors by which individuals are influenced. The technological stimulus consists of AI-enabled PMIS features, including explainability (e.g. LIME explanations), variable importance visualizations, and confidence indicators (Ribeiro et al., 2016).
- **Organism (O)** describes internal cognitive and emotional states of the users. These two connect stimulus and response. Based on trust in automation research (Lee & See, 2004; Mayer et al., 1995) and technology acceptance literature (Davis,

1989; Bhattacharjee, 2001), the organism can be defined as trust perceptions, perceived usefulness, and evaluation of system results.

- **Response (R)** is defined as behavioral outcomes. Response includes managerial reliance, decision integration, and subsequent performance improvements (Caniëls & Bakens, 2012; Raymond & Bergeron, 2008).

The flexibility of the SOR framework has been demonstrated in previous research. This means that the SOR framework acts well in modeling mediated behavioral relationships in information systems (Jacoby, 2002; Po-An Hsieh & Wang, 2007). As mentioned earlier, these studies focused on how environmental stimuli affects internal cognitive evaluations, which then shape behavioral responses. This logic is aligned with current studies modeling explainable AI features.

By applying the SOR perspective, and based on the descriptions in Sections 2.4 and 2.5, the framework clarifies these concepts:

- AI-enabled PMIS features, including explainability mechanisms as **stimuli**
- Trust as the **organism**
- Managerial reliance as the **behavioral response**

2.11 Identified Research Gaps

Based on the gap introduced in Chapter 1, this section provides details about the limitations of existing literature.

According to the literature review, a solid body of knowledge has been built across four areas: (1) information systems success theory, (2) project management information systems (PMIS) research, (3) trust and technology acceptance studies, and (4) explainable artificial intelligence (XAI). However, these areas have mostly been studied separately, and they have not fully integrated these concepts.

While a fundamental blueprint was developed for smart PMIS, trust calibration and explainability are still not fully addressed in this framework (van Besouw & Bond-Barnard, 2021). Similarly, existing IS success models ignored or overlooked project-specific factors. Therefore, the need for a trust-based framework is essential.

First, the traditional IS success models such as DeLone and McLean (2016) and later improvements (Petter et al., 2008; 2013; Gable et al., 2008) work well for standard systems. However, they were not designed for integrating AI features. They can evaluate system quality, information quality, use, user satisfaction, and net benefits. However, they do not support structural ambiguity, probabilistic outputs, or explainability. As PMIS increasingly uses machine learning, these models may not fully explain how users rely on them. Explainability as a crucial element expressing system success is not developed in these frameworks.

Secondly, PMIS research has focused on functionality and performance (Ahlemann, 2009; Caniëls & Bakens, 2012). More recent studies on Smart PMIS (Jaafari & Manivong, 1998; Oesterreich & Teuteberg, 2016) show increasing interest in intelligence and automation. However, only a few studies cover different aspects of managerial decisions. They also do not sufficiently evaluate and calibrate trust in high-stakes projects. The interaction between human and AI features in PMIS is still at a theoretical level.

Third, trust research in information systems and automation (Lee & See, 2004; Bhattacharjee, 2001; Venkatesh et al., 2003) shows that trust has a critical role in user adoption and continuous use. However, most studies examine general systems or consumer contexts. Trust in projects within the organizational scope is still limited, especially where decisions have financial, contractual, or safety consequences. In these contexts, calibrated trust, not just trust, is the key factor. The literature has not explained how explainability affects this calibration.

Fourth, the XAI literature mainly focuses on technical explanation frameworks (Ribeiro et al., 2016; Doshi-Velez & Kim, 2017; Hoffman et al., 2018). While user-centered evaluation has been discussed, few studies examine real-world, high-stakes professional settings. It is still unclear what types of explanations project managers consider useful, defensible, and actionable.

Finally, governance and PMOs' roles are rarely integrated into studies of AI-enabled PMIS (Hobbs & Aubry, 2007; Müller & Wang, 2024). As intelligent systems and AI can support decision-making, governance becomes essential. It is required to incorporate

transparency, auditability, and accountability in projects. The connection between PMO governance and explainable AI has not been fully studied yet.

Some practice-oriented frameworks such as CloudPedagogy AI Capability framework (n.d.) includes key components like AI capability, governance, and human–AI collaboration, but it only focuses on AI adoption and capability. There is no unified structure that is tailored specifically to AI-enabled project management information systems in construction industry.

All these gaps demonstrate a real need for a unified framework that connects the following concepts:

- AI-enabled PMIS
- Explainability
- Trust and calibrated trust
- Organizational governance structures
- Project manager performance

Existing research covers some parts but not the whole picture. A new integrated model is needed. This model should combine IS success theory, PMIS research, trust studies, and XAI for high-risk project settings like construction industry.

This thesis addresses the gap by positioning trust as the central factor. Explainability supports this trust and shapes managerial reliance and performance in AI-embedded PMIS.

2.12 Human–AI Collaboration in Project Management

It is obvious that moving toward smart PMIS should not be seen as replacing managers with automation. Instead, augmentation is emphasized in contemporary research. It is argued that digital technologies can strengthen human capabilities when they are designed as a complement to human strengths (Brynjolfsson & McAfee, 2014).

AI can process large databases, recognize patterns in scheduling, and predict cost deviations better than humans in project management. However, interpreting context and negotiating with stakeholders are still in the hands of individuals. Humans still need to make ethical judgments (Alvarenga et al., 2019).

PMIS can enhance project success when managers actively utilize system outputs for their decisions (Raymond & Bergeron, 2008). Moreover, decision-making systems work more efficiently when recommendations are critically evaluated by users before being applied to context.

Therefore, human–AI cooperation in PMIS depends on:

- clear analytical reasoning,
- the ability for managers to override the system,
- consideration of different scenarios,
- feedback loops that support learning and improvement.

Explainability acts as a bridge that makes collaboration possible. AI recommendations stay as external inputs if they do not provide understandable reasoning, and thus, they cannot be effectively integrated into managerial decisions.

2.13 Organizational Governance and Accountability in Intelligent PMIS

Governance becomes more essential as AI has become part of PMIS. Project Management Offices (PMOs) typically manage PMIS implementation and standardization (Hobbs & Aubry, 2007). These structures are helpful in integrating reporting practices and performance metrics throughout projects.

PMOs may vary in structure and strategic role, which affects how digital systems are adopted and enforced (Müller & Wang, 2024). In AI-enabled settings, PMOs are still responsible for ensuring that system outputs meet organizational standards for transparency and accountability.

Furthermore, alignment between organizational strategy and project activities is enabled by governance (Musawir et al., 2017). When project decisions are affected by AI, governance frameworks need to improve:

- data integrity and validity,
- auditability of decision logic,
- documentation of explanations,
- ethical considerations around algorithmic prioritization.

Thus, explainability can support managerial decisions as well as institutional compliance. The ability to defend decisions is just as critical as analytical precision in regulated industries such as engineering and construction.

2.14 Linking IS Success Theory with AI Explainability

The DeLone and McLean (2003; 2016) IS Success Model is one of the most influential models for evaluating information systems. It has six crucial elements:

- System quality
- Information quality
- Service quality
- Use
- User satisfaction
- Net benefits

AI-enabled PMIS present new features that earlier versions of IS success models are not able to handle. In particular, interpretability and trustworthiness in systems can directly affect system quality. System quality can then lead to actual use and expected benefits. Additionally, conceptual development of the antecedents of success is required. They are the main driver factors of success (Petter et al., 2013). In smart PMIS, explainability processes can act as enablers, which have a direct impact on system integrity and usefulness.

Furthermore, IS success models can be integrated with Task-Technology Fit (TTF). This indicates that performance outcomes depend on how well technology aligns with task requirements (Tam & Oliveira, 2016). Likewise, in AI-enabled PMIS, explainability improves this alignment since it allows managers to understand recommendations in their specific task contexts.

Therefore, this thesis extends IS success theory by presenting the following chain:

AI Capabilities → Explainability Mechanisms → Trust Perceptions → Use and Performance Outcomes

In this model, trust is considered as a mediator which links explainability and managerial decisions.

2.15 Synthesis of Theoretical Streams

Overall, the literature reviewed in this chapter reveals several interconnected themes:

1. **PMIS Evolution:** moving from reporting tools (PMBOK, 2017; Ahlemann, 2009) to integrated, intelligent frameworks (Jaafari & Manivong, 1998; Oesterreich & Teuteberg, 2016).
2. **IS Success Theory:** system quality alone is not enough. User perceptions and behavioral engagement are also critical factors (DeLone & McLean, 2016; Petter et al., 2013).
3. **Technology Acceptance and Continuance:** continued use is tied to perceived usefulness, satisfaction, and whether expectations are met (Bhattacharjee, 2001; Davis, 1989; Venkatesh et al., 2003).
4. **Trust and Automation:** appropriate reliance in high-risk projects depends on calibrated trust (Lee & See, 2004; Mayer et al., 1995).
5. **Explainable AI:** interpretability helps users build a mental model and supports accountability (Doshi-Velez & Kim, 2017; Hoffman et al., 2018; Ribeiro et al., 2016).

Despite the progress in these areas, there is limited research that brings them together in the context of AI-enabled PMIS in project-based organizations.

2.16 Summary and Conceptual Positioning of the Present Study

Based on all the literature studies reviewed, this thesis considers AI-enabled PMIS as socio-technical systems, where analytical capabilities, cognitive processes, and organizational processes are aligned.

The proposed conceptual framework in this thesis has five layers:

- **Technological Layer:** PMIS features that work with AI
- **Interpretive Layer:** explainability for transparency and understanding
- **Psychological Layer:** Building trust and calibrating it
- **Behavioral Layer:** reliance on AI and its integration in decisions-making
- **Outcome Layer:** project success and project manager performance

As discussed earlier, trust is the central link between explainable AI and managerial performance outcomes.

Therefore, this thesis integrates IS success theory, trust in automation research, and XAI principles to offer a theoretically strong framework specifically designed for project management contexts in the construction industry.

3 Methodology

3.1 Introduction

This chapter describes the research methodology applied to explore how explainable artificial intelligence (XAI) can be designed to support project management information systems. It also clarifies how trust can be calibrated in the context of high-accountability projects. As discussed earlier in Chapter 1 and Chapter 2, the research problem is linked to AI decision-making support, trust, explainability, and how managers rely on systems in project-based organizations.

A theoretical basis was built in Chapter 2. It developed a combination of Information Systems (IS) success theory, trust in automation research, explainable AI literature, and the Stimulus–Organism–Response (SOR) framework. This chapter activates the conceptual model by employing an empirical research design that provides insights from experienced project managers. Specifically, AI-enabled PMIS capabilities and explanation features are regarded as stimuli, trust perceptions and accountability concerns as organismic states, and reliance or override behaviors as behavioral responses.

A design-oriented and qualitative approach is applied. This method follows the logic of Design Science Research (DSR) (Hevner et al., 2004; Peffers et al., 2007). The primary goal is not only to describe but also to develop a conceptual trust-based explainability framework based on practical evidence. Following the principles of DSR, this thesis focuses on the early stages of artifact development. It includes identifying the problem, defining the solution, and developing a conceptual design. However, the technical implementation and evaluation are not within the scope of this study.

Due to the socio-cognitive nature of trust, a qualitative research strategy was chosen. It is also considered that explainability depends on context. Semi-structured interviews allow a better understanding of how project managers interpret AI-generated recommendations. They additionally help to understand how managers evaluate system reliability and manage accountability challenges under pressure in real projects. A hybrid deductive–inductive thematic analysis approach is used. It supports coding based on the

theoretical foundation developed in Chapter 2. However, it also remains open to new contextual insights that emerge from the data.

The chapter is organized into four parts. First, it clarifies the research framework and its alignment with DSR. Second, it describes the qualitative research design, sampling strategy, and interview procedures. Third, it explains the details of the thematic analysis process. This analysis is supported by NVivo 15 software and includes the hierarchical coding structure and rationale. Finally, it outlines ethical considerations, translation procedures, trustworthiness criteria, and limitations.

3.2 Research Questions

The study addresses the following research questions:

RQ1: How do project managers perceive trustworthiness in AI-enabled PMIS?

RQ2: What role does explainability play in building trust in AI-enabled PMIS?

RQ3: What user requirements are needed for a trust-based explainability framework for AI-enabled PMIS?

These questions are deliberately structured in this sequence. The first question clarifies how AI-enabled PMIS are perceived and how trust is formed. The second explores how explainability impacts trust calibration. Then, the outcomes learned from the data are translated into design requirements. As a result, they form the foundation of the conceptual artifact developed in Chapter 5.

3.3 Research Framework: Design Science Research

3.3.1 Positioning Within Design Science Research

This study adopts the Design Science Research (DSR) paradigm. DSR is a problem-solving research approach that creates artifacts such as models and frameworks to solve organizational and technological problems (Hevner et al., 2004). It is in contrast with explanatory research because it does not only describe or predict outcomes. Instead, DSR creates prescriptive knowledge in order to develop the artifacts (Gregor & Hevner, 2013; March & Smith, 1995).

This study designs an artifact, which is a conceptual trust-based explainability framework for AI-enabled PMIS. It is a suitable framework that connects:

- AI-enabled PMIS capabilities
- Explainability processes
- Trust formation and trust calibration
- Managerial reliance and decision integration

This artifact can be categorized as a model that represents the relationship among different concepts (conceptual relationships) to guide the overall design and its performance (March & Smith, 1995).

However, within the scope of this thesis, a system is not implemented or evaluated. It focuses on the early stages of DSR, as explained by Peffers et al. (2007):

1. Identifying problems
2. Defining solution objectives
3. Designing and developing the conceptual artifact

User-centered requirements are collected through practical interviews that shape the artifact. This approach makes sure that the resulting framework is not just based on theory but also on the practical knowledge of practitioners. Therefore, the research can be best described as a design-oriented qualitative study based on a DSR approach.

3.3.2 DSR Alignment with Research Questions

The diagram below shows how the methodology of this study is adapted to the DSR phases.

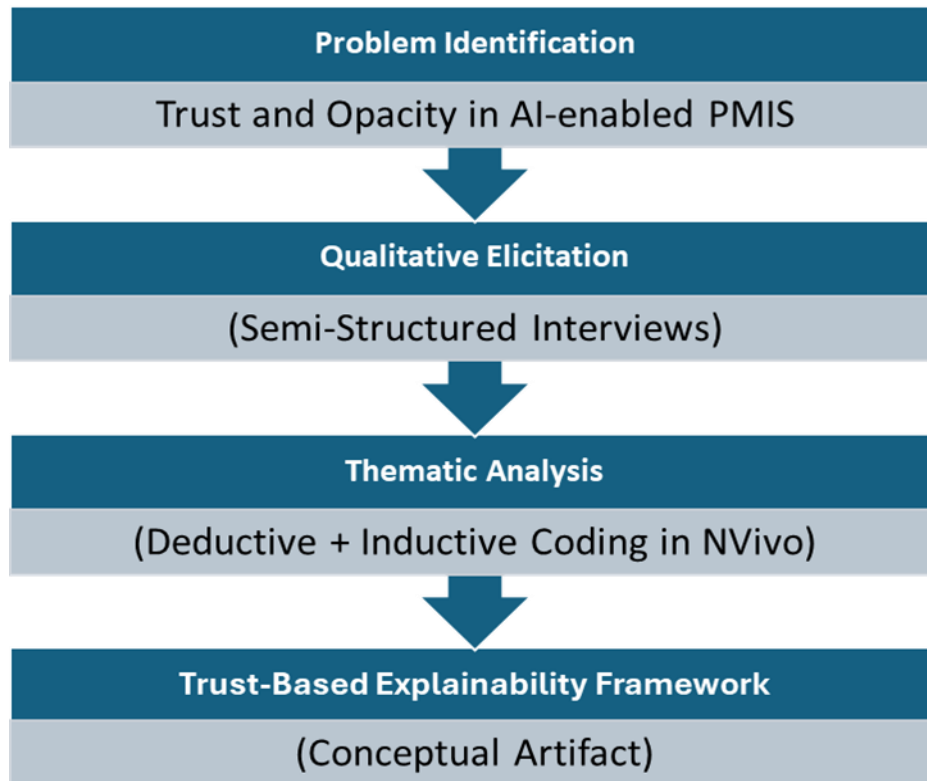


Figure 1. Methodological Positioning within Design Science Research.

This design ensures two things: the suggested framework is based on real data from professional project managers, and it is conceptually aligned with the theoretical model from Chapter 2.

3.4 Research Design

3.4.1 Qualitative Approach

A qualitative research design was chosen because the study focuses on a socio-cognitive approach (trust, accountability, explainability, and reliance). This approach depends on context and requires interpretation.

As mentioned in the previous chapter, trust in automation is a psychological state that reflects a willingness to rely on a system under uncertain conditions (Lee & See, 2004). Additionally, users' perceptions of system ability, integrity, and benevolence reflect trustworthiness (Mayer et al., 1995). If users can build mental models and understand the context, it means that explainability is effective (Hoffman et al., 2018; Doshi-Velez

& Kim, 2017). Without a contextual basis, these concepts cannot be achieved through quantitative methods alone.

Qualitative interviews allow project managers to explain:

- How they evaluate AI recommendations
- Why they accept or do not accept system outputs
- What explanations make decisions defensible in high-accountability settings
- How reliance is affected by organizational settings

It is essential to employ a detailed approach for shaping robust design principles, not just measuring surface-level acceptance.

3.4.2 Semi-Structured Interviews

Semi-structured interviews were chosen as the main method for data collection. This method combines structure with flexibility (Kvale & Brinkmann, 2009). Semi-structured here means that participants are allowed to let the conversation flow naturally, and the researcher may change the order of questions, adjust wording, and ask follow-up questions. However, at the end, the transcripts follow the intended flow of questions. All key components can be covered through a structured interview. This approach also allows participants to explain details and provide context. The interview consists of 22 questions across five themes:

1. Professional Background
2. PMIS and AI Exposure
3. Digitalization and Organizational Change
4. Trust and Evaluation of AI-Supported Decisions
5. Explainability Requirements and Design Expectations

3.5 Sampling Strategy

3.5.1 Target Population

The target interview group consisted of experienced project managers in project-based organizations in the construction industry. It mostly involved organizations with particularly high financial, contractual, and safety accountability.

Trust calibration becomes critical when organizations decisions involve material risks. Therefore, this context is highly relevant from a theoretical perspective.

3.5.2 Sampling Method

The sampling strategy was purposive, and participants with relevant experience were selected (Patton, 2014). They were chosen based on four criteria:

- Minimum of three years of project management experience
- Experience using PMIS
- Familiarity with AI-supported tools
- Willingness to participate

The target sample size was around ten participants. In focused qualitative research, thematic saturation is often obtained between approximately 12 and 15 interviews (Guest et al., 2006; Hennink & Kaiser, 2022). However, in this thesis, there were limitations in participant availability based on the defined criteria.

3.5.3 Participant Overview

The interview participants worked in medium to large construction companies across infrastructure and commercial sectors. They had various levels of familiarity with digital systems. Table 8 (in Chapter 4) shows their years of experience, sector, level of AI exposure, date of interview, and its mode.

In summary, the sample represented:

- Medium and large construction companies

- Infrastructure, residential, industrial and commercial sectors
- Different levels of digital maturity

Coding labels (PM01–PM10) were used to respect the anonymity of participants.

3.6 Saturation Strategy

Although qualitative studies are not designed to produce statistically generalizable results, thematic saturation is still difficult. In this thesis, saturation was assessed iteratively during analysis. Here, saturation means that new interviews do not produce new codes or new conceptual ideas related to the research questions.

This study did not rely only on a fixed number of interviews, and coding was conducted simultaneously with data collection. According to Guest et al. (2006) and Hennink and Kaiser (2022), the main sign that saturation has been reached is when the same themes keep coming up again and there is no new theme emerging.

Therefore, the sample size was determined based on actual analysis rather than relying on a fixed number of interviews. This means that despite challenges in finding suitable candidates based on the sampling criteria, the researcher did not fix the number of interviews at ten. Instead, the interviews continued until sufficient data had been collected.

3.7 Interview Protocol

The interview was categorized in five sections:

- **Section 1: Professional Background (Q1–Q4)**
Information related to interviewees' roles, experience, and the systems they used.
- **Section 2: PMIS and AI Exposure (Q5–Q8)**
Exploration of system familiarity and exposure to AI.
- **Section 3: Digitalization and Organizational Change (Q9–Q11)**
larger organizational changes and systematic challenges.
- **Section 4: Trust and Evaluation (Q12–Q16)**

Investigation of trust, hesitation, when users override the system, and accountability.

- **Section 5: Explainability and Requirements (Q17–Q21)**
design requirements and what types of explanations users prefer.
- **Closing Question (Q22)**
Open reflections.

The full interview guide is available in [Appendix 1](#).

Table 1. Mapping Interview Sections to Research Questions

| Research Question | Interview Questions |
|-------------------|---------------------|
| RQ1 | 12–16 |
| RQ2 | 17–20 |
| RQ3 | 17–21 |

3.8 Data Collection Procedures

All interviews were conducted in English, except for two interviews. These two were conducted in Finnish because it was more convenient for participants to answer in their native language. For these interviews, the transcripts were translated into English using a reliable translation application. The translations were then checked by the thesis supervisor, who is a native Finnish speaker, to ensure accuracy. Original Finnish and English transcripts were saved, and all translation scripts were also documented. The interviews were conducted between February and March 2026. All interviews were audio-recorded with participant consent and transcribed verbatim within one week of each session.

According to institutional policies and GDPR requirements, all data were securely stored. Interviews were conducted either in person or through Zoom online meetings. Two interviewees were met in person at their agreed locations, and the other eight interviews were managed via Zoom due to geographic distance across different cities in Finland or participant preference. Detailed interview information, including dates, durations, modes, and languages, is provided in Appendix 1, [Table A1](#).

Prior to the interviews:

- Participants received a link to the interview questions via Google Docs
- They were informed about their confidentiality

Each interview lasted approximately 40–60 minutes with a total of around 8 hours. Interviews were transcribed word-for-word. Codes (PM01 to PM10) were used to ensure participants' anonymity.

After each interview:

- Notes and transcripts were recorded and organized
- Feedback was documented
- Transcripts were anonymized

3.9 Data Analysis: Thematic Analysis

3.9.1 Analytical Approach

The retrieved data were analyzed based on Braun and Clarke (2006) thematic analysis procedure. The analysis followed the reflexive thematic analysis principles that were developed in their later work (Braun & Clarke, 2019). Additional practical guidance also supported the analysis process (Akramul Kabir, 2024). This process consists of six phases:

1. Familiarization with data
2. Generating initial codes
3. Exploring themes
4. Reviewing themes
5. Defining themes
6. Producing the report

Coding was conducted using both deductive and inductive approaches.

Theoretical concepts introduced in Chapter 2 were used for initial deductive coding:

- Trust dimensions (Mayer et al., 1995)
- Trust calibration (Lee & See, 2004)

- IS success constructs (DeLone & McLean, 2016)
- Explainable AI (Hoffman et al., 2018)
- Stimulus–Organism–Response framework (Jacoby, 2002)

Inductive coding was used to identify emerging themes. The reason is that these themes reflect contextual realities that are not fully covered in existing research.

3.9.2 Implementing the SOR Framework

To have a clear structure for analysis, the Stimulus–Organism–Response (SOR) framework was implemented.

Table 2. SOR Implementation in the Present Study

| SOR Component | Theoretical Meaning | Interview Focus | Analytical Role ¹ |
|---------------|--|-----------------|---------------------------------------|
| Stimulus | AI-enabled PMIS features and explanation | Q5–8, Q17–21 | Technological and interpretive inputs |
| Organism | Trust perceptions, accountability concerns, cognitive evaluation | Q12–16 | Psychological states inputs |
| Response | Reliance, override the system by users, integration into decisions | Q8, Q15 | Behavioral outcomes |

By applying this framework, findings can be connected to the development of conceptual artifacts.

3.10 Use of NVivo Software

NVivo is a qualitative data analysis software tool. This study used NVivo 15 to ensure a clear analytical procedure and an organized coding system (Limna, 2023).

NVivo supports the following capabilities:

- Hierarchical coding structure (Shanks, n.d.)
- Matrix coding queries (*Using a Matrix in NVivo – QDATRAINING*, n.d.)
- Case comparison (*Using a Matrix in NVivo – QDATRAINING*, n.d.)

¹ Here, analytical role means how each S-O-R component contributes to the interpretation of the data.

- Visualization of theme relationships(*Using a Matrix in NVivo – QDATRAINING*, n.d.)
- Audit trail documentation(Shanks, n.d.)

To identify the patterns matrix queries were used, these patterns are:

- Trust awareness by Experience level
- Explainability preferences by AI experience
- Behavioral change due to accountability pressures

It is important to consider that NVivo is a support traceable tool for analysis not a replacement for analysis.

3.10.1 Hierarchical Coding Framework

As discussed earlier, the coding framework is adapted to both theoretical concepts outlined in Chapter 2 and the interview structure. The structure is both deductive and inductive. Deductive initial expected parent nodes were chosen based on derived theoretical concepts (trust theory, trust calibration, IS success, explainability research, and SOR). Child nodes were also defined deductively as initial expected categories, shown in Table 3. These codes were then modified and merged based on the interview transcripts data. The researcher engaged with the data iteratively, through which new patterns and relationships were uncovered.

Table 3 below provides the details of hierarchical **initial** coding expected.

Table 3. Hierarchical NVivo Initial Expected Coding Framework

| Level 1 Parent Node | Level 2 Sub-Nodes | Level 3 Indicators | Academic Source |
|---|-----------------------|---|-------------------------------|
| 1. Professional Context | Role characteristics | Project size, complexity | Demographic variables |
| | Experience level | Years in PM | |
| | Sector | Construction | |
| 2. AI-Enabled PMIS Stimuli (SOR: Stimulus) | AI exposure | Forecasting tools, risk models | Bagozzi (1986); Jacoby (2002) |
| | Decision support type | Cost, schedule, risk | |
| | Explanation presence | Visualizations, logs, LIME explanations | |
| | Ability perception | Accuracy, reliability | Mayer et al. (1995) |

| Level 1 Parent Node | Level 2 Sub-Nodes | Level 3 Indicators | Academic Source |
|---|---------------------------------|-------------------------------|-------------------------------|
| 3. Trust Perceptions (SOR: Organism) | Integrity perception | Transparency, consistency | Mayer et al. (1995) |
| | Benevolence perception | Alignment with project goals | Mayer et al. (1995) |
| | Confidence level | Comfort with output | Lee & See (2004) |
| 4. Trust Calibration Mechanisms | Over-reliance | Blind acceptance | Parasuraman & Riley (1997) |
| | Under-reliance | Ignoring output | Dietvorst et al. (2015) |
| | Calibration boundary | When not to rely on | Lee & See (2004) |
| 5. Explainability Functions | Mental model support | Understanding logic | Hoffman et al. (2018) |
| | Error detection | Identifying wrong predictions | Hoffman et al. (2018) |
| | Uncertainty communication | Confidence intervals | Doshi-Velez & Kim (2017) |
| | Defensibility support | Audit trail, documentation | Hoffman et al. (2018) |
| 6. Behavioral Response (SOR: Response) | Reliance behavior | Integration into decision | Bagozzi (1986); Jacoby (2002) |
| | Override actions | Manual adjustment | |
| | Justification practices | Reporting rationale | |
| 7. Organizational Governance Context | PMO involvement | Policy enforcement | Hobbs & Aubry (2007) |
| | Accountability pressure | Client/auditor expectations | Musawir et al. (2017) |
| | Compliance structures | Documentation requirements | Musawir et al. (2017) |
| 8. IS Success Dimensions | System quality perception | Usability, speed | DeLone & McLean (2003) |
| | Information quality | Accuracy, relevance | DeLone & McLean (2003) |
| | Satisfaction | User experience | DeLone & McLean (2003) |
| 9. Emergent Themes (Inductive) | Context-specific trust triggers | Unique industry patterns | Data-driven |
| | Cultural factors | Finnish risk norms | Data-driven |
| | Unexpected tensions | AI vs experience | Data-driven |

The initial coding framework was based on theoretical concepts (trust theory, explainability research, IS success models, and the Stimulus–Organism–Response (SOR) framework). However, the final practical analysis of interviews showed that these predefined concepts did not exactly reflect interviewees' responses.

During thematic analysis and iterative coding, the codes were modified to better adapt to the interview data. Therefore, several theoretical codes were changed and merged. Some of them also were interpreted into broader themes.

For example, the concepts related to trust perceptions, trust calibration, and IS success were changed into broader themes such as Trust Factors and Distrust Triggers. explainability codes were modified to Explainability Preferences. Finally, governance and accountability were merged together and shaped Accountability Perceptions theme.

These changes focus on a hybrid deductive–inductive thematic analysis approach (Braun & Clarke, 2006). Theoretical concepts guided the initial coding, but the final themes were extracted from the real data.

Therefore, seven major themes were categorized, as presented in table 4 below. These themes synthesize the theoretical coding framework with patterns identified across participants' responses.

Table 4. Mapping of Theoretical Codes to Empirical Themes

| Theoretical Coding Categories (Chapter 3) | Empirical Themes (Chapter 4) |
|--|-------------------------------------|
| Trust perceptions, Trust Calibration, IS Success | Trust Factors / Distrust Triggers |
| Explainability functions | Explainability Preferences |
| Governance and Accountability | Accountability Perceptions |
| Behavioral response (use, override) | Human–AI Collaboration |
| IS success dimensions (usefulness, value) | AI Benefits |
| Implementation context | Implementation Barriers |

As a result of this adjustment, the final empirical themes were aligned with the initial theoretical constructs.

3.10.2 Rationale for Hierarchical Coding Structure

The final coding structure is based on six principles:

First, the analysis is organized at a micro level based on the SOR framework to guide the analysis. It is important to note that this framework is not meant to restrict the analysis. AI-enabled PMIS features and explanations are coded under “Stimulus,” trust-related perceptions under “Organism,” and reliance behaviors under “Response.” Therefore, there is consistency between empirical findings and the conceptual framework.

Second, trust theory (Mayer et al., 1995) breaks the “Trust Perceptions” node into sub-nodes. This supports a distinction between the ability, integrity, and benevolence components of trust, rather than considering trust as a single category.

Third, based on trust calibration research (Dietvorst et al., 2015; Lee & See, 2004; Parasuraman & Riley, 1997), separate calibration nodes are created to recognize over-reliance. It also captures movements toward algorithm aversion.

Fourth, explanation mechanisms are coded based on explainability research (Doshi-Velez & Kim, 2017; Hoffman et al., 2018). This clarifies the differences among functions such as cognitive support, error identification, uncertainty communication, and defensibility.

Fifth, to examine the effects of system quality features on trust formation processes in AI-enabled contexts, the IS success model is applied (DeLone & McLean, 2016).

Finally, for new and emerging contexts that cannot be predicted by existing theories, inductive nodes were included.

By organizing codes hierarchically, the analysis becomes transparent and traceable from raw data to their proper interpretation. These theoretical codes were then refined through iterative analysis into seven themes that are supported by the interviews data (presented in Chapter 4). This finally leads to the development of design requirements.

3.10.3 NVivo Analytical Procedures

In NVivo, the analysis procedure was performed as follows:

- Coding frequency analysis (Bazeley & Jackson, 2013; Limna, 2023)
- Matrix coding (e.g., experience level and trust perceptions) (Bazeley & Jackson, 2013; *Using a Matrix in NVivo – QDATRAINING*, n.d.)
- Co-occurrence analysis or coding comparison (e.g., explainability and trust calibration) (*Using a Matrix in NVivo – QDATRAINING*, n.d.)
- Concept mapping to visualize relationships between themes (Bazeley & Jackson, 2013)
- Reflexive analytical notes to document coding decisions (Bazeley & Jackson, 2013; Zamawe, 2015)

Using NVivo in this structure improves a clear and methodical coding procedure.

3.10.4 Distinguishing Concepts and Defining Analytical Boundaries

This thesis involves multiple theoretical concepts, including trust theory, trust calibration, IS success theory, explainable AI, and governance. Therefore, specific consideration was devoted to coding to avoid conceptual overlap.

Trust dimensions, including ability, integrity, and benevolence, are analytically distinguished from trust calibration. Trust calibration reflects a behavioral alignment mechanism rather than individual perception.

Moreover, IS success concepts (system quality, information quality, and satisfaction) are coded as contextual factors that influence trust formation. In contrast, they are not considered components of trust itself.

Explainability is coded in a way that differentiates it from trust dimensions. This prevents circular interpretation of findings.

This framework supports clear and distinct conceptual boundaries throughout the analysis.

3.11 Development of Design Requirements

After thematic analysis, the results are translated into artifact development through a structured interpretative process. It is important to note that not all themes can be automatically translated into design requirements. Therefore, some criteria are required to guide the selection of themes. Three specific criteria are considered:

1. Cross-case recurrence: The theme appears across several participants (Guest et al., 2006; Hennink & Kaiser, 2022).
2. Theoretical relevance: The theme connects to key concepts such as trust calibration or explainability (Braun & Clarke, 2006).
3. Design implication clarity: The theme provides practical system design changes or requirements (Gregor & Hevner, 2013; Peffers et al., 2007).

The selection of these three criteria is based on combining qualitative research principles and Design Science Research logic.

Themes that meet these criteria are used to develop design principles. This process shapes the trust-based explainability framework presented in Chapter 5.

The criteria answer three key questions, as summarized in table 5:

Table 5. Theme Selection Criteria

| Criterion | Question it answers |
|----------------------------|--|
| Cross-case recurrence | “Is this real in the data?” |
| Theoretical relevance | “Does this matter theoretically?” ² |
| Design implication clarity | “Can this be used to design something?” |

If a theme passes all three, it is worth for inclusion in the design framework.

3.12 Ethical Considerations

This study followed research ethics principles (Resnik, 2024). All interviewees were informed in advance about the purpose and procedures of the study, as well as the voluntary nature of their participation and their confidentiality. Participants provided their written consent by responding to the researcher’s email.

Participants received the interview questions in advance via Google Docs form. All participants’ names, workplace names, and project-specific details were omitted from transcripts and reports to ensure anonymity. No video or audio recordings were conducted in order to protect participants’ privacy. Transcripts were documented and accessed only by the researcher and her supervisor. The entire process was in alignment with GDPR and institutional data protection policies.

In the case of two Finnish-language interviews, the transcripts were translated into English by the researcher and checked by the supervisor. During the translation process, semantic meaning and contextual nuances were carefully preserved. The original Finnish transcripts were also documented for verification purposes.

² Does this finding help explain something important in the literature or framework (e.g., S-O-R, trust, accountability)?

3.13 Quality Criteria (Trustworthiness and Consistency)

Some qualitative criteria were considered to improve methodological quality. These criteria were derived from Lincoln and Guba (1985) trustworthiness framework:

Credibility

- Engagement with data over an extended period
- Regular discussion with supervisor per week
- Quote what participants said word by word to illustrate themes, support interpretations, and give authenticity to the analysis.

Transferability

- Detailed contextual descriptions were provided
- Participants' characteristics were documented

Dependability

- Maintain an Audit route
- Keep the full NVivo file
- Document the reflections continuously in a reflexive documentation note during analysis

Confirmability

- Coding decisions were documented
- Explain the justification of the theme selection and its relevance to theory.

3.14 Researcher Positionality and Reflexivity

As AI technologies are adopted worldwide across various fields and increasingly used in daily work, project managers find it difficult to avoid the role of AI-supported tools as advisors in decision-making. This makes the topic of this thesis highly relevant to the current needs of project managers.

The researcher has a background in project management and an interest in digital transformation. Although this background may be beneficial, it is essential to avoid pre-assumptions about the value of explainability or responsible AI. Therefore, reflective notes were documented during the analysis to support interpretive decisions and to reflect on potential biases.

3.15 Methodological Limitations

There are several limitations that should be noted:

- Sector-specific focus (Finnish construction): The study focuses specifically on the Finnish construction sector.
- Subjective participant reports: Findings are based on what participants told about their own experiences, not on direct observation
- Single-researcher coding: Coding was carried out by a single researcher.
- No technical system evaluation was applied.
- DSR limited to artifact conceptualization: The scope of the DSR contribution is limited to the development of a conceptual artifact, not a technical solution.

Later, the discussion of these limitations is provided in Chapter 5.

3.16 Chapter Summary

This chapter described the methodological framework in this study. The research uses semi-structured interviews and thematic analysis with NVivo to develop design requirements for a trust-based explainable framework.

The next chapter presents empirical findings from the thematic analysis of interviews and explains how trust and explainability are connected in AI-enabled PMIS in high-accountability project contexts.

4 Empirical Findings - Thematic Analysis

4.1 Introduction

This chapter presents the empirical findings derived from semi-structured interviews conducted with 10 project managers in construction industries. The interview transcripts were analyzed using NVivo 15 software. Additionally, the analysis follows the six-phase thematic analysis framework proposed by Braun and Clarke (2006).

The analysis answers the following research questions:

RQ1: How do project managers perceive trustworthiness in AI-enabled PMIS?

RQ2: What role does explainability play in building trust in AI-enabled PMIS?

RQ3: What user requirements are needed for a trust-based explainability framework for AI-enabled PMIS?

Seven major themes were identified through iterative coding in NVivo. These themes clarify patterns that show how construction project managers evaluate, trust, and interact with AI-enabled PMIS.

4.2 Overview of the Empirical Analysis

The thematic analysis revealed seven parent themes and several related sub-themes. NVivo was used to organize, code, compare, and review the interview data. Matrix coding queries were applied to identify patterns across participants. Furthermore, cluster analysis was used to explore relationships among the identified codes.

4.2.1 Coding Hierarchy

Seven parent nodes and twenty-nine child nodes were defined in NVivo for the analysis. The coding structure was based on a hybrid deductive–inductive approach. Parent nodes were initially extracted from the theoretical framework (e.g., trust theory, explainability research, and IS success models). They were then modified and merged through the thematic analysis of interview transcripts. Table 6 shows the parent themes and their analytical focus as below.

Table 6. Overview of Main Themes (Parent NVivo Codes and Their Description)

| Main Theme (Parent Codes) | Code Description |
|----------------------------------|--|
| Trust Factors | What builds trust in AI-enabled PMIS |
| Distrust Triggers | What causes doubts, rejection, or override of AI outputs |
| Explainability Preferences | What kinds of explanations users expect and value |
| Accountability Perceptions | Who is accountable for AI-supported decisions |
| AI Benefits | What values AI-enabled PMIS provides for users |
| Implementation Barriers | What barriers may hinder the use of AI-embedded PMIS in practice |
| Human–AI Collaboration | How users balance AI input with their own judgment |

As shown in Table 6, while defining the parent codes in NVivo, the focus was not only on trust itself. Instead, trust was interpreted into explainability, accountability, practical benefits, limitations, and the continued role of experts as the primary decision-makers.

Table 7 shows the hierarchy of coding. This classification displays the parent and their corresponding child codes, as well as their frequency of occurrence in the interview transcripts.

Table 7. NVivo Coding Hierarchy Summary

| Parent Coding | References | Key Child Coding |
|----------------------------|-------------------|---|
| Trust Factors | 98 | Transparency (30), Track Record (24), Alignment with Site Experience (22), Consistency (12), Vendor Reputation (10) |
| Distrust Triggers | 76 | Black-Box Outputs (26), Past Inaccuracies (18), Conflict with Site Reality (18), precision (8), Missing Context (6) |
| Explainability Preferences | 72 | Key Drivers (24), Confidence Scores (20), Visual Explanations (14), Drill-Down Capability (8), Comparable Cases (6) |
| Accountability Perceptions | 54 | PM Responsibility (26), Shared Accountability (18), Vendor Responsibility (6), Organizational Responsibility (4) |

| Parent Coding | References | Key Child Coding |
|-------------------------|------------|---|
| AI Benefits | 50 | Early Warning (18), Efficiency (14), Better Decisions (10), Resource Optimization (8) |
| Implementation Barriers | 42 | Data Quality (16), Integration Issues (12), Skills Gap (8), Cost for Small Firms (6) |
| Human-AI Collaboration | 20 | AI Augments (12), Humans Lead (8) |

The number of references shows that participants have emphasis on trust factors, distrust triggers, and explainability, which agrees with the focus of this study.

4.2.2 Participant Demographics

The participants are ten construction project managers who varied in their level of experience, work sector, and familiarity with AI tools. This variety provided a broader insight relevant to AI-enabled PMIS in real workplace. Table 8 summarizes the characteristics of the participants.

Table 8. Participants Overview

| Code | Role | Experience | Sector | AI Familiarity | Date | Mode |
|------|---|------------|-------------------------|-----------------|------------|-----------|
| PM01 | Construction PM - EPCM | 9 years | Industrial/EPCM | Moderate | 05.02.2026 | In person |
| PM02 | Senior Design & Construction Manager | 18 years | Consulting/ Renovation | Moderate | 15.03.2026 | Zoom |
| PM03 | Construction PM – Industrial | 15 years | Industrial Construction | Low to Moderate | 17.03.2026 | In person |
| PM04 | Construction PM | 18 years | Commercial/ Residential | Low | 19.03.2026 | Zoom |
| PM05 | Senior Project Planner – Infrastructure | 21 years | Infrastructure | Moderate | 22.03.2026 | Zoom |

| | | | | | | |
|------|--|----------|------------------------------|-----------------|------------|------|
| PM06 | Construction PM - Commercial & Public | 8 years | Commercial/ Public | Low to Moderate | 26.03.2026 | Zoom |
| PM07 | Construction PM | 8 years | General Con- struction | Moderate | 28.03.2026 | Zoom |
| PM08 | Construction PM - Industrial | 10 years | Industrial Con- struction | Moderate | 28.03.2026 | Zoom |
| PM09 | Construction PM - Residential | 12 years | Residential/ Commercial | Moderate | 29.03.2026 | Zoom |
| PM10 | Construction PM -Construction Technology | 6 years | Construction Technology | High | 29.03.2026 | Zoom |

4.2.3 Stakeholder-Specific Problem Patterns

Besides the seven main themes common among all participants, there were some differences based on the participants' sector, role, and level of experience with AI-enabled PMIS. These differences are not in contrast with the main themes, but they clarify how the concepts of trust and explainability are perceived by different project managers. Table 9 shows the problem patterns that are specific to different stakeholders.

Table 9. Stakeholder-Specific Problem Patterns

| Company Type/ Project Type | First Concern | Secondary Concern | Main Basis of Trust |
|---|---|--|--|
| Large infrastructure / EPCM projects | Data quality for multiple contractors | Integration into existing systems | Transparency and track record |
| Consulting / design- management | Implementation barriers across organizations | Balance between AI and humans' role | Explainability and learning from past feedback |
| Industrial / Residential | Site Reality Contradicts System recommendations | Subcontractor coordination | Alignment with site experience |
| Public / sensitive context | Accountability and auditability | Transparency for all stakeholders | Documentation and Audit Trails |
| Small firm / cost-sensitive con- text | Cost of AI tools for company | Integration into smaller projects | Simplicity and practi- cal value |
| Public / Construc- tion technology | Skills gaps and imple- mentation problems | Balance between AI and humans' role | Transparency |

Table 9 shows that AI-supported systems can be interpreted differently depending on the operational setting in which systems are used. For example, participants working in infrastructure and multi-contractor companies preferred data consistency and detailed explanations. In contrast, those working in the public sector emphasized auditability and defensibility. Additionally, some participants from smaller companies prioritized cost-effectiveness and practical relevance. Finally, those in larger organizations that had greater familiarity with AI focused more on learning, transparency, and collaboration between AI and individuals.

4.3 Word Frequency Analysis

The first step in analyzing the interview transcripts was a word frequency analysis, to identify terms that were commonly repeated across all interviews. This analysis provides a descriptive overview of frequently repeated words. However, it is only a supporting tool to initiate and inform the thematic analysis.

The most frequently repeated terms included “project” (128 occurrences), “system” (148), “data” (156) and “recommendations” (134). The word "site" appeared 80 times, which means the emphasis on construction industry. In addition, the term “trust” appeared 168 times. This means that trust plays a central role in how participants interpret and evaluate AI-enabled PMIS. However, the significance of these terms cannot be defined based on their frequency. Thematic coding and interpretation of participants’ responses are required to identify the themes and meanings within the data. Table 10 below shows the results of word frequency analysis.

Table 10. Most frequent words in Dataset (Top 20)

| Rank | Term | Occurrences | Context |
|------|----------------|-------------|--|
| 1 | trust | 168 | Central theme across all interviews |
| 2 | data | 156 | Quality, integration, fragmentation |
| 3 | system | 148 | PMIS tools and various platforms |
| 4 | recommendation | 134 | AI-generated recommendations |
| 5 | project | 128 | Key factors of analysis |
| 6 | AI | 122 | Artificial intelligence |
| 7 | decisions | 108 | Managerial decisions |
| 8 | understand | 94 | Need for explanations |
| 9 | experience | 88 | Professional judgment |
| 10 | confidence | 82 | Certainty in recommendations |
| 11 | site | 80 | Construction industry, On-site reality |
| 12 | explain | 78 | Explainability needs |
| 13 | recommend | 74 | System outputs |
| 14 | human | 60 | Human-AI collaboration |
| 15 | quality | 54 | Data and system quality |
| 16 | transparent | 48 | Logic of AI recommendations |
| 17 | risk | 44 | Project risks, predictions |
| 18 | schedule | 42 | Time management |
| 19 | subcontractor | 38 | Construction-specific stakeholders |
| 20 | responsible | 36 | Accountability |

4.4 Cluster Analysis

As a supporting approach, cluster analysis was used to identify the relationships among the coding. This method groups the codes that appear across the whole dataset. This shows how different concepts are connected. The result of the cluster analysis shows that concepts like transparency, data quality, and explanation are all connected to one

single process, which is trust-building. However, black-box outputs, missing context, and past inaccuracies are tied to distrust-factor themes. Construction-sector concepts such as site experience and real-world project conditions created another grouping. Therefore, contextual alignment is essential in developing trust in AI-enabled PMIS.

Cluster analysis not only shows the usual relationships but also supports the interpretation of patterns identified through thematic analysis.

The cluster analysis groupings are as below:

Cluster 1: Trust-Transparency Group

- Transparency
- Data Quality
- Key Drivers
- Confidence Scores
- Missing Context
- Trust Factors

Cluster 2: Distrust-Past Errors Group

- Black-Box Outputs
- Past Inaccuracies
- Distrust Triggers
- Over-Precision

Cluster 3: Human-AI Collaboration Group

- AI Augments
- Humans Lead
- Better Decisions
- Early Warning
- Skills Gap

Cluster 4: Accountability Group

- PM Responsibility
- Shared Accountability
- Organizational Responsibility

Cluster 5: Site Reality Group

- Alignment with Site Experience
- Conflict with Site Reality
- Integration Issues

Key Observations can be summarized as below:

- **Transparency** is clustered with **Trust Factors**, showing that transparency is the main factor of trust.
- **Black-Box Outputs** and **Past Inaccuracies** grouped with **Distrust Triggers**, showing them as the key distrust factors.
- **Site-related codes** (Alignment with Site Experience, Conflict with Site Reality) together, showing how important real site conditions are in construction sector.
- **PM Responsibility** and **Shared Accountability** clustered together, showing that participants saw accountability as more complex than just one person being responsible.

Figure 2, derived from NVivo reports, shows how the main concepts group together based on the cluster analysis.

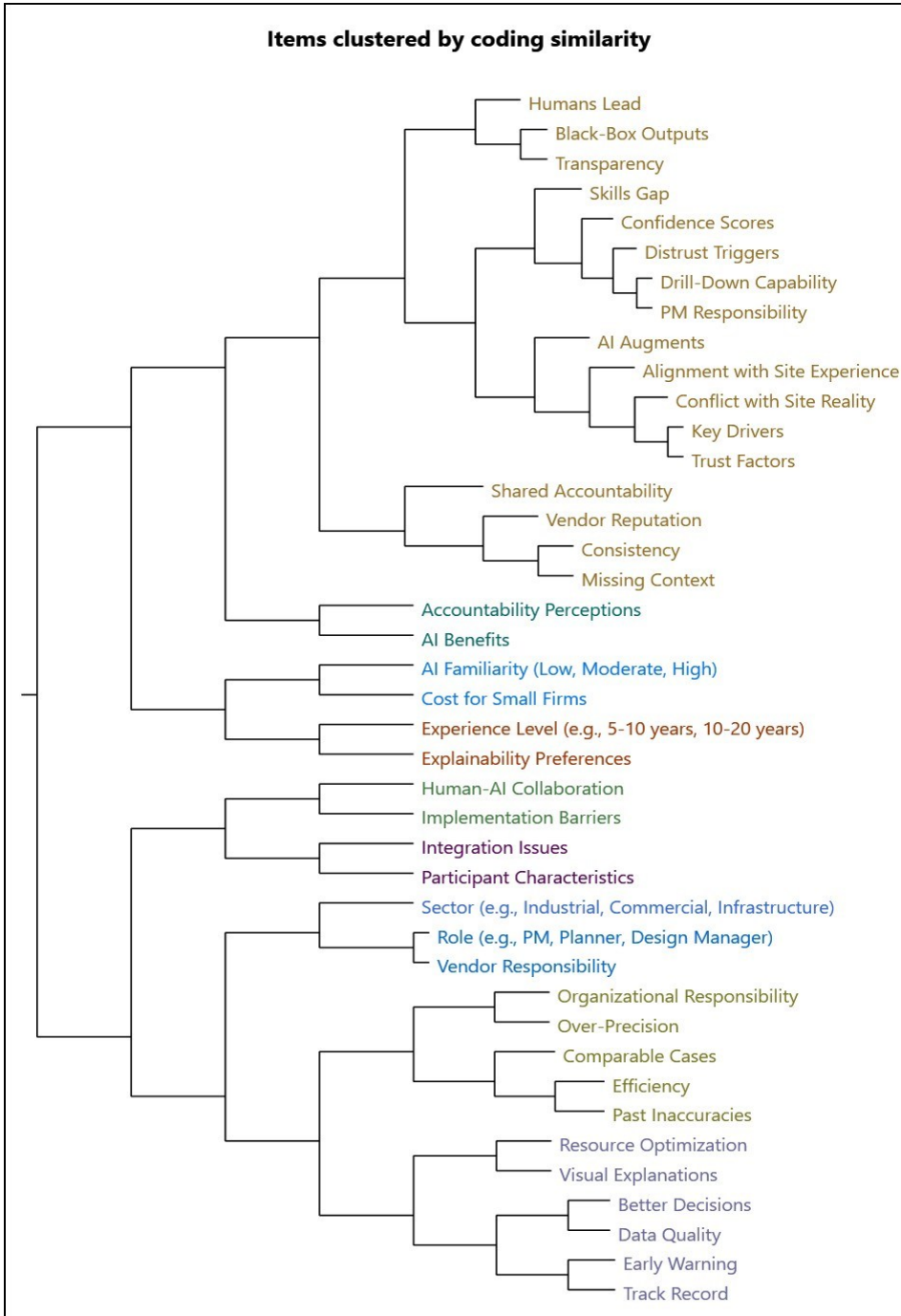


Figure 2. Cluster Analysis dendrogram diagram from NVivo

4.5 Matrix Coding Query

A matrix coding query was used to see whether the themes were observed across all participants' interview transcripts. Table 11 shows the themes across participants.

Table 11. Matrix Coding Query (Themes Across Participants)

| Theme | PM01 | PM02 | PM03 | PM04 | PM05 | PM06 | PM07 | PM08 | PM09 | PM10 | Total |
|-------------------|------|------|------|------|------|------|------|------|------|------|-----------|
| Trust Factors | 3 | 3 | 2 | 8 | 10 | 5 | 10 | 23 | 23 | 11 | 98 |
| Distrust Triggers | 11 | 6 | 2 | 7 | 4 | 2 | 15 | 9 | 11 | 9 | 76 |
| Explainability | 2 | 2 | 2 | 9 | 10 | 11 | 8 | 7 | 13 | 8 | 72 |
| Accountability | 4 | 6 | 5 | 3 | 7 | 5 | 6 | 8 | 5 | 5 | 54 |
| AI Benefits | 4 | 0 | 5 | 6 | 5 | 0 | 7 | 5 | 8 | 10 | 50 |
| Barriers | 3 | 4 | 7 | 4 | 0 | 3 | 5 | 6 | 7 | 3 | 42 |
| Human-AI | 0 | 4 | 4 | 1 | 2 | 2 | 0 | 1 | 4 | 2 | 20 |

Table 11 shows that the three most frequent themes among all participants are trust factors, distrust triggers, and explainability preferences, each with different levels of emphasis. Accountability came up in every interview, and this shows a strong agreement that responsibility should remain with humans. Other themes, such as implementation barriers and human–AI collaboration, appeared less than others. This variation shows differences in organizational development, exposure to AI, and individual experience.

4.6 Theme 1: Trust Factors - Transparency as Foundation (98 references)

The first major theme focuses on what builds trust in AI-enabled PMIS. Among all participants, trust was interpreted through sub-concepts such as transparency, track record, and alignment with real site experience. This theme responds to the first research question (RQ1). This shows how project managers realize trustworthiness in AI-enabled systems.

4.6.1 Transparency (30 references)

Transparency was the most important factor for building trust. Participants mentioned that they needed to understand the reasoning behind AI recommendations to trust them.

"Transparency is key. If I can see the reasoning, which factors influenced the recommendation, what assumptions were made. I trust it more. On site, I need to know why the system is suggesting something." (PM01, EPCM)

"If the AI can show me its reasoning and data sources, I am more likely to trust it. If it is a black box, I am skeptical." (PM05, Infrastructure)

"Opening up the reasoning logic is certainly interesting. Highlighted sources are good because you can familiarize yourself with them and draw your own conclusions." (PM02, Consulting)

Several participants explained that transparency needs to be specific for construction sector. They added that AI recommendations should be explained in a way that site personnel can understand.

"I need to understand the reasoning. For a delay prediction, show me: which activities are at risk, why (weather? materials? labor?), and the confidence level." (PM01, EPCM)

4.6.2 Track Record (24 references)

Participants described that trust was built over time through consistent accuracy of AI outputs. They trusted the AI system more when they could see reliable performance across multiple projects.

"Proven track record. if the system has been accurate historically, trust builds. But in construction, each project is unique. historical data only goes so far." (PM04, Residential)

"When the AI confirms my own analysis, confidence increases. When it suggests something unexpected, I investigate. often finding factors I hadn't considered." (PM09, Residential)

"If it provides more similar outcomes to what I have experienced before, then it might increase confidence." (PM07, General Construction)

4.6.3 Alignment with Site Experience (22 references)

One theme relevant to the construction industry was alignment with site experience. Participants mentioned that they trusted AI recommendations when these were consistent with their professional experience gained over years of working on construction sites.

"Alignment with site reality is most important. If the recommendation makes sense given what I see on site, I trust it." (PM03, Industrial)

"If the AI's recommendation aligns with my 15 years of industrial concrete experience, I trust it more. If not, I ask the AI for its sources and then verify with my site team." (PM03, Industrial)

"I rely on my 18 years of experience. I ask: Does this feel right for this specific building?" (PM02, Consulting)

4.6.4 Consistency (12 references) and Vendor Reputation (10 references)

Consistency in recommendations and the vendor's reputation were also mentioned by some participants as factors of trust shaping. Vendor reputation refers to the perceived credibility and reliability of the AI system provider.

"If the system's recommendations align with good practice and produce good outcomes over time, trust grows." (PM09, Residential)

"Established companies with construction-specific expertise are trusted more. Generic software vendors are viewed skeptically." (PM06, Commercial)

4.7 Theme 2: Distrust Triggers - The Site Reality Gap (76 references)

The second major theme in the interviews was the factors that intensify distrust in AI-enabled PMIS. Participants mentioned that black-box recommendations, conflicts with site reality, past inaccuracies, and over-precision are the factors that create distrust. This theme responded to the first research question (RQ1). It explained what makes project managers question or reject AI recommendations.

4.7.1 Black-Box Outputs (26 references)

The most common reason that created distrust was not being able to understand how the AI system generated its recommendations. Participants explained that they could not accept recommendations without explanations.

"Black-box outputs make me hesitate. If the system says :do this, without explaining why, I'm skeptical. On site, I need to know why." (PM01, EPCM)

"Black-box algorithms are a red flag. If the system can't explain itself, I'm doubtful." (PM10, Construction Tech)

"If the system cannot tell me where it got its information, I hesitate." (PM06, Commercial)

4.7.2 Conflict with Site Reality (18 references)

One distrust factor in the construction industry was when AI recommendations ignored or contradicted physical site conditions. Participants mentioned that sometimes AI systems overlook what is really happening on the project site.

"When recommendations ignore site realities, like suggesting work when the site is inaccessible or materials haven't arrived." (PM03, Industrial)

"The system once recommended accelerating concrete pours based on weather forecasts. But I knew the site had access issues that week, a local event closing road. The recommendation was technically sound but practically impossible." (PM01, EPCM)

"I doubt system advice when recommendations don't match project context. Professional judgment and team input are then essential." (PM05, Infrastructure)

4.7.3 Past Inaccuracies (18 references)

Some mistakes in AI recommendations that led to errors causing schedule delays or cost overruns also created distrust. Participants mentioned several examples of times when the systems were wrong.

"If the system was wrong before, I'm cautious about relying on it again. Trust is hard to rebuild." (PM04, Commercial)

"It has led to flawed forecasts or incorrect resource allocation in some cases." (PM01, EPCM)

4.7.4 Over-Precision and Missing Context (14 references combined)

Over-certainty and missing contextual factors were also mentioned as distrust factors.

"False certainty undermines trust. Construction is inherently uncertain. The system said 95% confidence, but we all knew it was a guess." (PM09, Residential)

"AI cannot capture all relevant factors, political issues, community concerns, client relationships. Systems that ignore context generate untrustworthy recommendations." (PM02, Consulting)

4.8 Theme 3: Explainability Preferences - What Construction Managers Want (72 references)

The third theme observed was the types of explanations that project managers would expect from AI-enabled PMIS. This theme responded to the second and third research questions: RQ2 (the role of explanation in building trust) and RQ3 (user requirements for a trust-based framework).

4.8.1 Key Drivers (24 references)

Participants in the interviews mentioned that they needed to know the effective factors in AI recommendations.

"I need to know the key factors for recommendation. For a delay prediction, show me: which activities are at risk, why (weather? materials? labor?), and the confidence level." (PM01, EPCM)

"I want to see which specific site activities or supply chain events caused the alert." (PM07, General Construction)

"I need to know the reasons. what factors are leading to the recommendation, with weights." (PM10, Construction Tech)

4.8.2 Confidence Scores (20 references)

Participants mentioned that they needed to know the level of certainty. This was an essential factor for calibrated trust. They needed numerical values to show how certain the AI was.

"Certainty level should be standard. If the system says 70% confidence due to weather uncertainty, I know to be cautious and monitor conditions." (PM09, Residential)

"If it expresses the uncertainty level, it would be better. we might know what percent you can trust." (PM08, Industrial)

"Confidence scores with clear thresholds, maybe green/yellow/red." (PM05, Infrastructure)

4.8.3 Visual Explanations (14 references)

Construction project managers in the interviews mentioned that they preferred explanations in visual formats, such as graphs and charts.

"Visual explanations help. Gantt charts with risk overlays, heat maps of problem areas." (PM01, EPCM)

"Converting things into visual form. AI is good at providing illustrative images for presentations instead of just text." (PM02, Consulting)

"Clear visualization and explainable outputs would increase my confidence." (PM05, Infrastructure)

4.8.4 Drill-Down Capability (8 references) and Comparable Cases (6 references)

Participants needed multi-level explanations, for example, summaries for quick decisions and detailed explanations whenever they needed them. They also mentioned they needed to compare the explanation for a project with similar projects.

"Both, depending on context. For quick site decisions, simple explanations with key factors and confidence scores work. For major decisions, I need detailed justifications. The system should provide summary with the option to access deeper information." (PM09, Residential)

"I would like to see different cases. This recommendation is based on similar projects with similar conditions." (PM05, Infrastructure)

4.9 Theme 4: Accountability Perceptions - Who Is Responsible? (54 references)

Another main theme in the interview transcripts was accountability for AI-supported recommendations. This theme also responded to the first research question (RQ1) and showed who is responsible when AI recommendations support decision-making in projects.

4.9.1 PM Responsibility (26 references)

Almost all participants agreed that project managers remain responsible for project decisions, even when AI recommendations are applied.

"Ultimately, the project manager. We're the decision-makers. The system is a tool, it can be wrong, but we choose whether to follow its advice." (PM01, EPCM)

"The project manager carries ultimate responsibility. We're on site, we know the context, we make the final ca

ll." (PM09, Residential)

"The project manager who made the decision is finally responsible." (PM05, Infrastructure)

"Based on my personal experience, if a mistake occurs in a decision, responsibility falls directly on the project management team and the project manager." (PM04, Commercial)

4.9.2 Shared Accountability (18 references)

Some participants mentioned that accountability can also be shared with organizations, vendors, and customers alongside the project managers.

"The person who prompts the AI is responsible for the mistake. You cannot blame the tool. It's the user who is accountable." (PM07, General Construction)

"The organization is responsible for selecting appropriate tools and providing training. System providers are responsible for systems working as designed. Project managers are responsible for how they use the tools." (PM10, Construction Tech)

"If the system was poorly designed or its limitations were not clearly communicated, the company behind the system has responsibility." (PM09, Residential)

4.9.3 Vendor and Organizational Responsibility (10 references)

Participants also mentioned vendors and organizational responsibility for the use of AI recommendations, although this was discussed less than other forms of accountability.

"The technology can be outdated, and it may not understand the tasks, so it can be the system or the creators." (PM01, EPCM)

"Management must also be competent and able to doubt AI-produced data if it seems exceptional." (PM02, Consulting)

4.10 Theme 5: AI Benefits in Construction (50 references)

The fifth main theme was the benefits of AI in PMIS within the construction industry. This theme answered the third research question (RQ3). It shows the key advantages that AI systems provide for project managers.

4.10.1 Early Warning (18 references)

One of the significant benefits they mentioned was AI's ability to identify risks and other problems before they become serious issues.

"For risk assessment, I feel confident using AI for reducing risk and preventing money loss." (PM08, Industrial)

"It helps us move from reactive to proactive management." (PM05, Infrastructure)

"The AI risk module has flagged potential delays based on weather patterns and subcontractor performance history. This has helped me adjust schedules proactively." (PM09, Residential)

4.10.2 Efficiency (14 references)

Participants in interviews believed that AI could manage the daily tasks and reduce manual work.

"It makes routine tasks easier to work. I spend less time on data collection and more time on verification and mitigation." (PM01, EPCM)

"It makes decision-making faster. I used to do similar decision-support with manual research. Now AI makes this faster and more comprehensive." (PM10, Construction Tech)

"The calculation template has reduced a huge amount of waste." (PM02, Consulting)

4.10.3 Better Decisions (10 references) and Resource Optimization (8 references)

Some participants mentioned that AI can help them improve decision quality and optimize resource allocation.

"Some insights improve decision quality. We catch risks earlier, allocate resources better." (PM05, Infrastructure)

"When the AI confirms my own analysis, confidence increases. This has generally improved my decision quality." (PM09, Residential)

4.11 Theme 6: Implementation Barriers - Construction-Specific Challenges (42 references)

Another theme was the barriers to AI adoption in the construction industry. This theme answered the third research question (RQ3). It shows why project managers do not use AI-enabled PMIS.

4.11.1 Data Quality (16 references)

The most significant issues mentioned by project managers were the quality of the data and the way AI sorted the data in a disconnected or fragmented way.

"Data quality is the biggest challenge. If site teams don't update progress accurately, the recommendations are useless." (PM01, EPCM)

"With multiple contractors and consultants, data comes in different formats and quality levels." (PM02, Consulting)

4.11.2 Integration Issues (12 references)

One major problem was how AI could be integrated with the systems that organizations were already using in their projects.

"System integration is poor. Different tools don't work with each other well. I spend too much time manually transferring data." (PM01, EPCM)

"Integration with existing workflows, not another extra tool to learn." (PM10, Construction Tech)

4.11.3 Skills Gap (8 references) and Cost for Small Firms (6 references)

Some participants mentioned that they did not have the proper skills to work with AI systems, such as prompting skills. Additionally, adopting an AI system creates extra costs for organizations, especially when the firm is small.

"But prompting skills are by far the biggest issue." (PM07, General Construction)

"Some experienced site supervisors struggle with tablets and software. They'd rather use paper." (PM09, Residential)

"For small companies like ours, cost is a barrier. Sophisticated AI tools are expensive." (PM04, Commercial)

4.12 Theme 7: Human-AI Collaboration in Construction (20 references)

The ideal relationship between project managers and AI system was another theme in interviews. This theme responded to the second and third research questions (RQ2 and RQ3). It shows that the human role in decision-making should not be omitted, and that AI should act as a counsellor rather than a decision maker.

4.12.1 AI Augments (12 references)

Participants always mentioned that AI is a supporting tool, not a replacement for project managers.

"AI should strengthen our judgment, not replace it. On site, conditions change constantly. AI can't capture all that." (PM01, EPCM)

"AI should be used for efficiency, not as a replacement for professional judgment." (PM02, Consulting)

"AI should be a tool, not a crutch." (PM09, Residential)

4.12.2 Humans Lead (8 references)

Participants emphasized that final decisions should be made with project managers, especially for decisions where safety and relationships are at risk. Relationships here refer to cooperation and interactions between different stakeholders, clients, and team members, which cannot be managed by AI systems. Unlike cost or schedule, which can be measured with data, safety and relationships depend on human experience.

"AI should be a counselor or mentor, not the decision-maker." (PM08, Industrial)

"The best results come from human-AI collaboration. AI handling data processing, humans providing context and judgment." (PM10, Construction Tech)

"AI should make an agenda for me. I evaluate and accept or ignore it." (PM08, Industrial)

4.13 Theme Interconnections Analysis

The thematic analysis conducted in NVivo showed that the seven themes are not separate; but they create a connected chain of problems and solutions.

4.13.1 Primary Connection Chain: Data Quality → Trust → Adoption

Poor data quality reduces AI accuracy, which results in lowers trust, and then leads to limited adoption. This pattern was observed in some interviews.

"Data quality is the biggest challenge. If site teams don't update progress accurately, the recommendations are useless." (PM01, EPCM)

By analyzing the co-occurrence of Data Quality and Trust Factors using a matrix coding query in NVivo, these two codes appeared together in approximately 72% of coded references.

4.13.2 Secondary Connection Chain: Black-Box AI → Distrust → Overrides

Distrust increases when the logic behind AI recommendations is not transparent for project managers. As a result, project managers like to override its recommendations. Participants did not want technical information alone. They wanted explanations to clarify the recommendations based on project realities, data sources, and assumptions.

"Black-box outputs make me hesitate. If the system says 'do this' without explaining why, I'm skeptical." (PM01, EPCM)

The NVivo matrix coding query for checking co-occurrence shows that Explainability Preferences and Distrust Factors appeared together in 82% of cases.

4.13.3 Accountability Connection Chain: PM Responsibility → Need for Justification → Need for Explainability

This circular pattern shows that project managers, as the main accountable persons in projects, need to justify AI recommendations, which means those recommendations must be defensible.

"The project manager carries ultimate responsibility. We're on site, we know the context, we make the final call." (PM09, Residential)

NVivo Evidence shows that Accountability and Explainability appeared together in 78% of cases.

Other themes interconnections are summarized in Table 12 below:

Table 12. Cross-Theme Relationships

| Relationship | Interpretation |
|---|---|
| Transparency → Trust | Explanations make recommendations more understandable and reliable. |
| Missing Context / Complexity → Distrust | Lack of traceability and contextual relevance leads to rejection or override |
| Site Reality ↔ Acceptance of AI Output | Recommendations are trusted when they are in agreement with real site information |
| Explainability → Accountability Support | Explanations help users defend AI-supported decisions |

As shown in Table 12, trust is shaped when transparency, accountability, contextual understanding, and human expertise come together.

4.14 Synthesis of Findings

4.14.1 Summary of Key Findings

The key findings from the thematic analysis of the ten construction project managers interviewees are summarized in Table 13 below:

Table 13. Summary of Key Findings

| Theme | Core Finding | Key References |
|--|---|----------------|
| Theme 1: Trust Factors | Trust is built on transparency, track record, and alignment with site experience | 98 |
| Theme 2: Distrust Triggers | Distrust is influenced by black-box outputs, site reality conflicts, and past inaccuracies | 76 |
| Theme 3: Explainability Preferences | Construction managers want key drivers, confidence scores, and visual explanations | 72 |
| Theme 4: Accountability Perceptions | PMs accept that they are the main person in charge, but they also recognize shared accountability | 54 |
| Theme 5: AI Benefits | AI provides early warning, efficiency, and better decisions in projects | 50 |
| Theme 6: Implementation Barriers | Data quality and integration problems are the biggest challenges for AI adoption | 42 |
| Theme 7: Human-AI Collaboration | AI should augment, not replace, human decision | 20 |

Table 14 shows a heatmap with visual block lengths to summarize the matrix coding query results among stakeholders, who are grouped into five categories based on their role and company size.

Table 14. Matrix Coding Query - Themes by Stakeholder Type

| Theme | Large Infra-structure / EPCM (n=2) PM01, PM05 | Consulting / Design (n=2) PM02, PM10 | Industrial (n=2) PM03, PM08 | Public / residential (n=2) PM04, PM06 | Small Firm / Cost-Sensitive (n=2) PM07, PM09 |
|-------------------------|--|---|--------------------------------|--|---|
| Trust Factors | 13 | 14 | 25 | 13 | 33 |
| Distrust Triggers | 15 | 15 | 11 | 9 | 26 |
| Explainability | 12 | 10 | 9 | 20 | 21 |
| Accountability | 11 | 11 | 13 | 8 | 11 |
| AI Benefits | 9 | 10 | 10 | 6 | 15 |
| Implementation Barriers | 3 | 7 | 13 | 7 | 12 |
| Human-AI Collaboration | 2 | 6 | 5 | 3 | 4 |

This matrix shows that the group of small firm participants emphasized Trust Factors and Distrust Triggers. This likely reflects their higher sensitivity to trust issues due to resource constraints. Industrial participants highlighted Implementation Barriers, which may be because of the practical challenges of AI adoption on construction sites. Public sector participants needed Explainability more than others, along with transparency and auditability, likely because their projects are funded by governments. Large infrastructure and consulting participants showed equal interest in almost all themes.

4.14.2 Summary of Findings based on Research Question

To answer the research questions, the findings can be mapped to each of them, as shown in Table 15 below.

Table 15. Mapping of Findings to Research Questions

| Research Question | Relevant Themes | Key Findings |
|---|-------------------|--|
| RQ1: How do project managers perceive trustworthiness in AI-enabled PMIS? | Themes 1, 2, 4 | Trust is shaped based on transparency, a good track record, and alignment with the reality of site experiences. Distrust comes from black-box outputs and when AI suggestions oppose site reality. Project managers are responsible if they use AI-supported systems in decision making. |
| RQ2: What role does explainability play in building trust? | Themes 3, 7 | Explainability is crucial for trust. Project managers need key drivers, confidence scores, visual explanations, and drill-down capability. AI should improve human decisions. |
| RQ3: What user requirements are needed for a trust-based explainability framework? | Themes 3, 5, 6, 7 | Key requirements are: transparency, connection to site reality, confidence scores, audit trails, visual explanations, learning from feedback, and the ability to adapt to different levels of complexity in various projects. |

These themes satisfy the criteria from Chapter 3. They appear across multiple participants, build on trust and explainability research, and clearly inform the design of AI-enabled PMIS.

4.15 Chapter Summary

This chapter presented the findings from the thematic analysis through NVivo, based on ten semi-structured interviews with construction project managers with different levels of expertise. As explained in detail, seven major themes emerged throughout the analysis, so that they could answer the research questions. Finally, the chapter defined how these themes can shape a trust-based framework for explainable artificial intelligence in project management information systems, specifically in the construction industry. A summary is provided as below:

1. Trust is built on transparency, track record, and alignment with the site reality.
2. Distrust comes from black-box outputs, site conflicts, and past mistakes.

3. Managers want layered explanations, this means key drivers, confidence scores, and visual explanations aids.
4. Project managers are eventually responsible, but they also consider shared accountability.
5. AI offers some benefits, such as early warnings, efficiency, and better decisions.
6. Data quality and integration of AI into the system of organizations are the biggest barriers.
7. AI should support project managers in decision making, not replace them.

These findings help shape a trust-based explainability framework for AI-enabled PMIS in construction, which is presented in Chapter 5.

5 Discussion and Trust-Based Explainability Framework

5.1 Introduction

This chapter connects the empirical findings and theoretical foundations to develop a trust-based explainability framework for AI-enabled Project Management Information Systems (PMIS) in the construction industry in Finland. Before discussing the findings, a summary of the research questions, literature reviews and key empirical results is provided.

Three research questions were the basis of this study: (RQ1) How do project managers perceive trustworthiness in AI-enabled PMIS? (RQ2) What role does explainability play in building trust? (RQ3) What user requirements are needed for a trust-based explainability framework?

The literature reviews can be summarized in four areas: information systems success theory, trust in automation research, technology acceptance literature, and explainable AI. The literature review identified the following gaps: traditional PMIS success models cannot address black-box outputs, PMIS research has overlooked project managers' role in evaluating AI recommendations, research related to trust has ignored the project context, XAI has focused only on technical advancement, not professional settings, and governance structures have had no place in studies of AI-supported PMIS.

In this research, the Stimulus-Organism-Response (SOR) framework (Bagozzi, 1986; Jacoby, 2002) was applied. This framework considered AI-enabled features as stimuli, trust perceptions as organismic states, and managerial reliance as behavioral responses. The methodology involved semi-structured interviews with 10 project managers in the construction industry, based on the Design Science Research (DSR) framework. The interview transcripts were analyzed using thematic analysis via NVivo 15. The results revealed seven major themes, which are explained in the following sections in order to answer the research questions.

The chapter has three main goals. First, it connects the findings to the research questions and the theoretical perspectives. These theoretical concepts were trust, explainability, IS success, governance, and human–AI collaboration. Second, the findings define the

design requirements and the components of the trust framework. Third, it discusses the contributions of this study to theory and practical application. Finally, it explains the limitations of the research and suggestions for future research.

Based on Design Science Research (DSR) framework, practical insights are used to shape the conceptual development of an artifact. In this study, the artifact is a trust-based explainability framework for AI-enabled PMIS. The framework reflects the user's needs. These needs were expressed by experienced construction project managers.

The chapter is structured to move from theory to application. Section 5.2 discusses the findings to respond to the research questions. Section 5.3 synthesizes the findings into design requirements. The proposed framework is presented in Section 5.4. Section 5.5 discusses the theoretical implications of the study. Section 5.6 explains the practical implications. Finally, section 5.7 presents the limitations of the study and Section 5.8 presents some suggestions for future research.

5.2 Discussion of Findings

5.2.1 Project Managers' Perceptions of Trustworthiness in AI-Enabled PMIS

The first research question was how project managers identify the trustworthiness in AI-enabled PMIS. The findings show that trustworthiness is not considered alone for evaluating a system. However, it is defined as a socio-technical judgment. Five factors shaped this judgment: transparency, previous system performance, contextual fit, professional experience, and accountability expectations.

The findings explain that project managers trust AI-supported recommendations when the system is transparent, when its outputs are consistent with previous performance, and when recommendations are aligned with site reality. This supports the theory in Chapter 2 that trust in intelligent systems is not based only on technical ability. Integrity and practical usefulness also matter in a defined context. Mayer et al.'s trust dimensions can clarify this: ability means perceived analytical competence, integrity shows itself in transparency and consistency, and benevolence can be translated to whether recommendations are aligned with project goals and realities.

The literature on trust in automation is also confirmed here. Lee and See (2004) argue that calibrated trust leads to appropriate reliance, not blind trust. Participants in this study confirmed this. They consistently evaluated AI recommendations against their own knowledge, previous project experience, and site conditions. Therefore, trustworthiness in AI-enabled PMIS is conditional, especially in the construction industry. In this sector, decisions have financial, contractual, and safety consequences.

One important empirical contribution of this study is the identification of what can be described as the site reality gap. Recommendations can be technically reasonable but still be rejected because they do not consider site conditions, delays of subcontractors, access problems, weather challenges, stakeholder pressures, or other contractual problems. This finding goes beyond the literature review for trust. It shows that in construction project management, trust cannot be separated from the reality and context of the project site.

The findings also explain the practical procedure project managers use to evaluate AI-generated recommendations. They compare them with previous project experience and then verify them against site conditions. Therefore, trust is not passively accepted but is constructed actively by a validation process. In contrast, when recommendations lack transparency and conflict with site realities, trust will not be formed. Trust also breaks down when there is a background of past inaccuracies.

5.2.2 The Role of Explainability in Building Trust

The second research question was about the role of explainability in building trust in AI-enabled PMIS. The findings reveal that explainability is a key factor to form trust, calibrate trust, and use AI recommendations accountably. Participants in interviews mentioned that they tend to use AI-supported recommendations when they can understand the logic behind them. They needed to know the key drivers, uncertainty level, and references for data sources.

This finding agrees with the literature reviewed. Ribeiro et al. (2016) emphasize that output should be interpretable for understanding predictions. However, Hoffman et al.

(2018) argue that explanations should help users form a mental model, detect errors, and develop appropriate reliance. This study confirms these functions in a project management context. Although it is also important that participants did not want only technical explanations. They wanted explanations that could support practical reasoning, verification, defensibility, and communication with others.

Another key finding was revealing the concept that explainability is more than one factor. Project managers wanted multiple forms of explanation. They required key drivers, confidence scores, visual representations, comparable cases, and drill-down capability. Therefore, explainability should be adapted to the context in which the user applies it. A short explanation might be enough for daily tasks and decisions on the site, but stronger justifications are needed when there is strategic, contractual, financial, or safety risk in decisions.

The connection between explainability and accountability became clear in this research. Since project managers are still responsible for project decisions even when AI-supported recommendations are used, they need explanations that help them justify their decisions. Based on explanations, they can follow the recommendations, question them, or override them. Therefore, explainability is not only about comprehension but also about professional defensibility.

5.2.3 User Requirements for a Trust-Based Explainability Framework

The third research question was what user requirements should be met for a trust-based explainability framework for AI-enabled PMIS. The findings conclude that: the standard transparency is not enough for project managers. They need a framework that helps them trust based on context, rely wisely, get layered explanations, and make accountable decisions. In other words, transparency alone is not the goal. What matters is whether the framework helps managers navigate real-world complexity. Can it adapt to different decision contexts? Does it help them calibrate their trust appropriately? Can they access explanations at the right level of detail when they need them? And more importantly, does it support the accountability they already have?

Six major requirement categories were identified. First, the system needs transparency and reliable reasoning and traceable data sources or the origins of data. Second, it should honestly confess the uncertainty level without wrong precision. Third, it cannot ignore site realities and actual conditions in projects. Fourth, it must provide the explanation that matches the complexity of decisions. Fifth, accountability for using AI recommendations needs documentation, history of projects and decisions path, and outputs that can be defended. Sixth, it must improve, not replace, human decisions.

These requirements are completely in parallel with the theoretical background in Chapter 2. In terms of IS success, explainability acts as a design feature that strengthens several dimensions. It improves system quality and how beneficial users find the system. It contributes to user satisfaction. The SOR framework also offers another way to understand this concept. AI-enabled PMIS features and explanations act as stimuli. Trust perceptions and accountability function as organismic states. Over-reliance or override behaviors represent the response. The practical findings reinforce and validate the SOR framework. It provides a clear way to show how explainability eventually shapes trust. In addition, it is not enough for an explanation to be understandable. It should also be defensible. Clients, contractors, and senior managers may all ask for justification. Therefore, explanation elements should cover two different needs: internal reasoning and external justification. Usability alone is not sufficient. Professional responsibility still plays a critical role in decision-making.

5.3 Translating Findings into Design Requirements

Based on the DSR logic laid out in Chapter 3, the findings define design requirements for the final conceptual artifact. The findings are extracted from the themes that were repeated in all interview transcripts and theories in Chapter 2. Design requirements are summarized in Table 15 below.

Table 16. Design Requirements based on Empirical Findings

| Empirical Finding | Design Requirement | Justification |
|---|--|---|
| Trust depends on transparency | The AI system should explain how recommendations are generated. | Users need to understand the reasons behind the recommendations before relying on them. |
| Trust is affected by black-box outputs | The system must not produce black-box outputs. It must make its reasoning traceable. | Vague outputs lead to hesitation, rejection. |
| Site reality increases trust | Context of projects are important. The system must reflect project realities and actual site conditions. | Recommendations that ignore practical realities are distrusted. |
| Confidence scores are needed | The system must clearly indicate how confident it is in its recommendations. | Users must be able to see not only how confident the system is, but also where its limitations are. |
| Different decisions require different levels of explanation | The system must provide layered explanations. | Daily small decisions should come with brief summaries. Major decisions need more details. |
| Accountability remains with PMs | The system must support auditability and defensibility. | Project managers must justify AI-supported decisions to other stakeholders. |
| AI is preferred as supporter, not replacement | The system must enable human to judge and assess outcomes. | AI should collaborate with users, not take over them. |
| Data quality is a major barrier | The system must indicate data quality. | Users must be alerted when data quality issues affect recommendation. |

| Empirical Finding | Design Requirement | Justification |
|--|---|---|
| Integration problems reduce usefulness | The system must work well with existing PMIS workflows and tools. | Different tools reduce trust, adoption, and efficiency. |
| Skills gaps affect adoption | Usability should never be sacrificed for complexity. Interfaces and explanations must remain clear. | Practical usability is necessary for trust and continued use of system. |

5.4 Proposed Trust-Based Explainability Framework for AI-Enabled PMIS

5.4.1 Framework Purpose

Based on the practical findings and the theoretical foundations, this thesis proposes a trust-based explainability framework for AI-enabled PMIS in the construction industry in Finland. The purpose is to help design AI-supported PMIS that are not just analytically powerful but also easy to understand, defensible, and usable in high-risk project contexts. Based on this framework, trust in AI-enabled PMIS is shaped in five layers: technological capability, explainability design, contextual validation, accountability support, and human–AI collaboration. How these layers interact defines whether users can accept AI recommendations or instead reject and question them.

5.4.2 Main Components of the Framework

The framework consists of key following components:

1. AI Capability Layer

The first layer covers the PMIS's analytical capabilities: budget and financing plan, risk prediction, scheduling support, resource allocation, abnormality detection, and decision recommendations. This shapes the foundation of the system. However, these capabilities do not mean that trust automatically follows.

2. Explainability Layer

The second layer includes explanations that help project managers interpret AI outputs. This layer translates the technical capability into information that is understandable and usable.

This layer includes:

- key drivers behind recommendations
- traceable data sources and their references
- reasoning logic
- confidence scores
- uncertainty levels
- visual explanation tools
- drill-down capability (the option to move from summary to detail)
- comparable past cases

This layer meets the needs of understanding and defensibility of AI recommendations.

3. Contextual Alignment Layer

The third layer is about the context. In the construction sector, AI recommendations should be in agreement with real project and site conditions. The findings show the reason why a recommendation can be technically correct but still rejected if it contradicts the realities.

This layer explains:

- site condition information
- specific limitations of project
- subcontractor and supply chain problems and realities
- Integration into Existing systems
- Alignment with All Stakeholder and Clients' Expectations

This layer bridges the site reality gap.

4. Accountability and Governance Layer

The fourth layer shows that decisions supported by AI should be part of governance structures of organizations. Because project managers have the final responsibility, the system must help them justify decisions, track outcomes, and produce auditable records.

This layer has:

- audit trails (history of previous projects and decisions path)
- explanation documentation
- documented assumptions
- defensible reasoning for clients and other stakeholders

This layer makes sure explainability supports accountability, in both the individual and the organization level.

5. Human–AI Collaboration Layer

The fifth layer provides the answer to the question that what role AI should play? AI provides decision support, not a replacement for managerial decisions. Project managers use AI for complex and huge amounts of data or repetitive tasks, but they insist on keeping final decision authority. This layer consists of:

- managers at the center of control
- collaborative decision making
- scenario explanation
- AI designed for reflection, not automatic operation

This layer prevents both over-reliance and under-reliance on AI recommendations.

5.4.3 Framework Logic

The logic of this framework can be summarized as follows:

AI capabilities produce recommendations, but recommendations alone are not enough.

Explainability makes AI recommendations understandable.

Contextual alignment makes recommendations usable in real world contexts.

Accountability support makes them defensible.

Human–AI collaboration ensures that managers are still in charge of decisions making.

The interactions among these layers result in **trust**. Then, trust influences whether project managers actually use AI recommendations in their decisions.

Table 17. Trust-Based Explainability Framework Structure

| Framework Layer | Main Function | Expected Outcome |
|-------------------------------------|---|--|
| AI Capability Layer | Generate recommendations | Possibility of Decision-support |
| Explainability Layer | Make outputs understandable and traceable | Understanding and Processing information |
| Contextual Alignment Layer | Fit outputs to site and project realities | Practical acceptability |
| Accountability and Governance Layer | Support justification and defensibility | Responsible use |
| Human–AI Collaboration Layer | Protecting the project manager's final say and the ability to reject AI recommendations | Calibrated reliance |

5.4.4 Framework Principles

The framework has six design principles:

- **Principle 1: Transparency**

For every AI recommendation, the system should clarify what the reason behind it was, what factors caused it, and what data was used and from which source.

- **Principle 2: Sensitivity to Project and Site Conditions**

Users need to interpret recommendations based on the specific project and site conditions.

- **Principle 3: Uncertainty Level**

AI-supporting systems should honestly admit their limitations, how confident the responses are, and identify the areas of uncertainty or ambiguity.

- **Principle 4: Layered Explainability**

The system should customize the explanation complexity level. The explanation depth should be adapted to the decision's complexity and importance.

- **Principle 5: Supporting Accountability**

Every AI recommendation needs to provide a clear explanation in a way that makes it possible to defend it, document it, and audit it.

- **Principle 6: Human at the Center of Decision-making**

The role of AI is to support, not replace the manager's role, especially in cases where safety and high risks exist.

5.5 Contributions to Theory

Based on theoretical contributions mentioned in chapter 1, this study provides some theoretical implications in five different areas. First, it reframes how project managers evaluate the PMIS. Two traditional factors, system quality and information quality, are no longer sufficient for PMIS evaluation. The research findings show that two new factors should be involved in design requirements: trust and explainability.

Second, it considers trust in automation research in more depth. How does trust calibration work in project management? The answer is that it needs more than perceived system competence. Contractual agreement, stakeholder analysis, and practical uncertainty should all be considered. So, trust needs awareness of real project conditions and accountability as well.

Third, it explains that XAI research needs to move beyond technical modification. Construction managers do not want just accurate responses. They want explanations that are practical, based on real context, defensible, and flexible enough for different decision situations.

Fourth, it expands IS success theory. Explainability is a design factor that explains how users perceive system quality, its usefulness, and satisfaction. Additionally, whether they tend to continue using the system's recommendations.

Finally, it emphasizes the SOR framework. The findings show that AI-enabled capabilities and explanations act as stimuli, trust and accountability also act as organismic states, and reliance or override behaviors can be the response. Future research can use this as a conceptual fact to initiate their research.

5.6 Practical Implications

The practical benefits of this study can be categorized into four groups, which can be applicable for software designers, PMOs, construction companies, and organizations using AI-enabled PMIS.

Software designers need to move beyond recommendation quality. The system needs layered explanations, contextual fit, visible uncertainty, and auditability. These are the features that should be incorporated into new AI-enabled systems.

PMOs and governors should consider that explainability in AI-enabled PMIS is about organizational responsibility. PMOs should define clear processes for documenting, reviewing, and defending AI-supported recommendations.

Construction companies or enterprises also need to consider that adoption barriers are not only technological. Lack of users' skills, and misalignment with project realities can all reduce trust. They need to invest in integrating with existing systems, training users, and adapting to older systems.

Finally, project managers can have great collaboration with AI systems in PMIS. AI provides support in early warning, analysis, and decision making. However, the final decision remains with project managers.

5.7 Limitations of the Study

Five main limitations accompany this study in the scope of this research.

Sample and context: The datasets come from only 10 project managers working in Finnish construction companies in Finland. This provides depth in this context relevance, but it cannot be generalized.

Data type: The findings are based on interviews, which means self-reported data, not direct observation of AI-supported decisions. The study collects what participants mentioned in interviews about what they need and experience. The researcher did not independently see the behavioral outcomes.

Coding approach: A single researcher defined the coding in NVivo and the interpretation. For better outcomes in NVivo, multiple coders are needed. They would add stronger depth in thematic analysis to see whether the results would be the same.

Conceptual framework: The study introduces a conceptual framework. It does not check or evaluate whether this framework would work in real situations and PMIS environments. This research can help design procedures, but it is not validated in real projects.

Temporary essence of AI: AI tools are changing rapidly. User expectations may vary in the future, and AI system capabilities will also evolve over time.

However, it is important to mention that these limitations do not weaken or invalidate this study. They clarify what the boundaries are and where the findings can be applied.

5.8 Suggestions for Future Research

Based on this research, several future research directions can be suggested.

1. Test in different industries. This study was limited to the construction industry. Would this framework work in infrastructure, energy, manufacturing, IT projects? Future research may find the answer.

2. Quantitative Study. This could be a quantitative study as well. The framework can have some measurable variables. Researchers could then test how explanation quality influences trust calibration, reliance behavior, and performance outcomes with quantitative metrics and achieve numerical outcomes.

3. Build a prototype. A prototype can be built in a real PMIS environment. It can be evaluated by user testing and simulations.

4. Compare stakeholder groups. Different groups may have different explainability needs. Project managers, PMOs, clients, contractors, and suppliers may need different kinds of explanations.

5. Governance. There might be some challenges regarding organizational policies, regulations, city laws and AI privacy concerns. All these factors affect the adoption of explainable AI in PMIS. This area is quite unexplored.

6. Tracking the change in trust definition. Trust definitions may change over time when project managers gain more experience with adapting to AI systems. Future research may need to track how the same users over time could behave when trust in AI-enabled PMIS evolves with repeated exposure to its recommendations.

5.8.1 AI-Generated Future Research Suggestions*

To have a complementary analysis of future research opportunities and to check whether all new potential dimensions have been considered, a comparison was made with the help of Microsoft 365 Copilot. This tool was used to generate new ideas for future research suggestions based on the findings of this study. The detailed prompt and responses from Copilot are provided in [Appendix 2](#). During prompting, it was ensured that the full scope of the study was clearly introduced to the AI, and all existing

researcher suggestions were mentioned to avoid redundancy. The future research suggestions generated by Copilot are summarized below (Microsoft Copilot, 2026) :

1. Creating a feedback loop addressing the site reality gap

Communicating the reality on the site to the system allows AI recommendations to update and learn in real time.

2. Create a “trust calibration” metric for construction PMIS

Measure the difference between perceived and actual accuracy of AI recommendations based on site conditions.

3. Compare the explanation timing for pre-decision vs. post-decision

Focus on explanation timing and examine the effect of pre- or post-decision explanations on trust and accountability.

4. The effect of certainty level format on trust (numeric, verbal, visual).

Examine how the type of presentation style impacts reliance on AI advice.

5. Showing how distrust builds up over multiple AI wrong recommendations.

Examine whether one major error or several small ones lead to distrust.

6. trade-off analysis between the type of explanation depth and time pressure

Which layers of explanation are needed when managers need to make decision quickly.

7. Examine the hierarchy impacts on trust in AI recommendations (e.g., PMOs, clients).

Study if AI advice is more likely to be rejected when it conflicts with a superior’s opinion.

8. Cultural Differences in AI Trust

Examine the trust definition among various countries and cultures.

9. Quantify the cost of distrust (delays, rework, overrides)

Calculate financial impacts of ignoring correct AI advice due to distrust.

10. Analyzing the integration of emotion and intuition in trusting AI advice

Understanding whether emotional drivers (stress, risk aversion, past project failures) can influence trust.

*All AI-generated suggestions were reviewed and aligned with the study's findings. They are just supplementary insights and not the main research contributions.

5.9 Chapter Summary

This chapter connected the empirical findings to the theoretical foundations of the thesis and introduced a trust-based explainability framework for AI-enabled PMIS in construction in Finland. The chapter discussed that trust is highly linked to transparency, past performance of similar projects, alignment with context, accountability, and the role of human in final decisions. Explainability is not a side factor, but a central factor to shape trust. It also supports appropriate reliance, and defensible project decisions.

As mentioned earlier, this framework has five layers: AI capability, explainability, contextual alignment, accountability and governance, and human–AI collaboration. These layers explain how AI recommendations can be applied in various projects if they provide understandable and usable recommendations, especially when there are high risks involved in projects.

At the end, the theoretical and practical advantages as well as limitations of this study were discussed. It was followed by some suggestions for possible research opportunities for the future. Overall, the primary point of this study is that AI-enabled PMIS needs a proper connection between AI outputs, human judgment, real project context, and accountability structures.

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Appendix 1. Semi-Structured Interview Protocol

This appendix contains the complete interview protocol used for data collection in this study. It includes the participant invitation, the interview structure, the full list of questions (English and Finnish), and the mapping of questions to the research objectives and Design Science Research framework.

1. Participant Invitation Letter

Dear Sir/Madam,

My name is Nasim Mahmoudi. I am currently pursuing a master's degree in strategic project management at the University of Vaasa, Finland. I have over 11 years of experience as a Project Manager, mainly in water and wastewater infrastructure projects.

Throughout my career, I have worked with various project management systems and witnessed how technology can impact decision-making and project outcomes. This experience inspired my master's thesis on **A Trust-Based Framework for Explainable AI in Project Management Information Systems**. My research explores how project managers trust and use AI-supported systems, and what kind of explanations they need to make better decisions.

As part of my academic research, I am conducting expert interviews with experienced project managers. Participation is voluntary, and all responses will be used solely for academic purposes.

If you have any questions, suggestions, or insights, feel free to contact me at nasim-mahmoudi.m@gmail.com.

I truly appreciate your time and support. Thank you so much for considering my request.

Yours sincerely,

Nasim Mahmoudi

University of Vaasa

nasimmahmoudi.m@gmail.com

2. Interview Purpose and Structure Thesis Title:

A Trust-Based Explainability Framework for AI-Enabled Project Management Information Systems (PMIS)

Purpose of the Interviews:

These semi-structured interviews aim to explore how project managers perceive, trust, and use AI-supported PMIS in practice, and what kinds of explanations are required to support trustworthy decision-making. The interviews support a Design Science Research (DSR) approach by eliciting user requirements for a trust-based explainability framework.

Interview Structure:

The interview is divided into five sections:

- Professional Background
- PMIS and AI Exposure
- Digitalization and Change in Project Management
- Perceptions of AI-Supported Decision-Making
- Explainability and Requirements

3. Full Interview Questions

Section 1: Professional Background

| English | Finnish |
|--|---|
| 1. Can you briefly describe your current role and responsibilities in project management? | 1. Voitko lyhyesti kuvailla nykyistä rooliasi ja vastuitasi projektinhallinnassa? |
| 2. How many years of experience do you have in project or construction project management? | 2. Kuinka monta vuotta kokemusta sinulla on projekti- tai rakennushankkeiden hallinnasta? |
| 3. What types of projects do you typically work on (e.g., size, complexity, sector)? | 3. Minkä tyyppisissä projekteissa tyypillisesti työskentelet (esim. koko, monimutkaisuus, toimiala)? |
| 4. In your current projects, how frequently do you rely on system-generated recommendations when making decisions? | 4. Kuinka usein luotat järjestelmän tuottamiin suosituksiin tehdessäsi päätöksiä nykyisissä projekteissasi? |

Section 2: PMIS and AI Exposure

| English | Finnish |
|---|---|
| 5. How would you describe your experience with Project Management Information Systems (PMIS)? | 5. Miten kuvailisit kokemustasi projektinhallinnan tietojärjestelmistä? |
| 6. Have you encountered AI-based or data-driven features in PMIS or other project tools? | 6. Oletko törmännyt tekoälypohjaisiin tai datavetoisiin ominaisuuksiin PMIS-järjestelmissä tai muissa projektityökaluissa? |
| 7. In which types of project decisions would you feel confident relying on AI-supported recommendations, and in which would you hesitate? | 7. Millaisissa projektipäätöksissä kokisit voivasi luottaa tekoälypohjaisiin suosituksiin, ja millaisissa tilanteissa epäröisit niiden käyttöä? |
| 8. How comfortable do you feel using system-generated recommendations in your daily work? | 8. Kuinka mukavaksi tunnet itsesi käyttäessäsi järjestelmien tuottamia suosituksia päivittäisessä työssäsi? |

Section 3: Digitalization and Change in Project Management

| English | Finnish |
|---|--|
| 9. How has the introduction of AI-supported recommendations changed your decision-making process, if at all? | 9. Miten tekoälypohjaisten suositusten käyttöönotto on muuttanut päätöksentekoprosessiasi, jos se on muuttanut sitä? |
| 10. In what ways have AI-supported systems influenced your confidence in project decisions? | 10. Millä tavoin tekoälyä hyödyntävät järjestelmät ovat vaikuttaneet luottamukseesi projektipäätöksiä tehdessäsi? |
| 11. What challenges have you experienced specifically when interpreting or relying on AI-generated recommendations? | 11. Millaisia haasteita olet kohdannut erityisesti tulkitessasi tai hyödyntäessäsi tekoälyn tuottamia suosituksia? |

Section 4: Perceptions of AI-Supported Decision-Making

| English | Finnish |
|---|---|
| 12. When a system provides a recommendation or prediction, how do you usually evaluate it? | 12. Kun järjestelmä antaa suosituksen tai ennusteen, miten yleensä arvioit sitä? |
| 13. When an AI-supported PMIS provides a recommendation, what factors influence whether you interpret it as reliable or questionable? | 13. Kun tekoälyä hyödyntävä projektinhallintajärjestelmä antaa suosituksen, mitkä tekijät vaikuttavat siihen, pidätkö sitä luotettavana vai kyseenalaisena? |
| 14. What makes you hesitate or doubt system-generated advice? | 14. Mikä saa sinut epäröimään tai epäilemään järjestelmän tuottamaa neuvoa? |
| 15. Have you ever overridden or ignored a system recommendation? Why? | 15. Oletko koskaan ohittanut tai jättänyt noudattamatta järjestelmän suositusta? Miksi? |
| 16. In your opinion, who is responsible when an AI-supported decision turns out to be wrong? | 16. Kenen mielestäsi pitäisi kantaa vastuu, kun tekoälytuettu päätös osoittautuu vääräksi? |

Section 5: Explainability and Requirements

| English | Finnish |
|---|--|
| 17. What specific types of explanation (e.g., reasoning logic, data sources, uncertainty levels) would increase your trust in an AI-supported recommendation? | 17. Millaiset selitykset (esimerkiksi päättelylogiikka, käytetyt tietolähteet tai epävarmuuden taso) lisääisivät luottamustasi tekoälypohjaiseen suositukseen? |
| 18. Do you prefer simple explanations or detailed justifications? Why? | 18. Pidätkö enemmän yksinkertaisista selityksistä vai yksityiskohtaisista perusteluista? Miksi? |
| 19. What information would you need to defend an AI-supported decision to colleagues or stakeholders? | 19. Mitä tietoja tarvitsisit puolustaksesi tekoälytuettua päätöstä kollegoille tai sidosryhmille? |

| | |
|--|---|
| 20. How should AI systems communicate uncertainty or limitations? | 20. Miten tekoälyjärjestelmien tulisi viestiä epävarmuudesta tai rajoituksista? |
| 21. If you could design an ideal AI-supported PMIS, what features would increase your trust? | 21. Jos voisit suunnitella ihanteellisen tekoälytuetun PMIS-järjestelmän, mitkä ominaisuudet lisääisivät luottamustasi? |

4. Closing Question

| | |
|---|--|
| English | Finnish |
| 22. Is there anything else you would like to share about AI, trust, or decision-making in project management? | 22. Onko vielä jotain muuta, mitä haluaisit jakaa tekoälystä, luottamuksesta tai päätöksenteosta projektinhallinnassa? |

5. Mapping to Research Questions and DSR Framework

Mapping to Research Questions

| Research Question | Corresponding Interview Questions |
|---|-----------------------------------|
| RQ1: How do project managers perceive trustworthiness in AI-enabled PMIS? | 12-16 |
| RQ2: What role does explainability play in building trust? | 17-20 |
| RQ3: What user requirements are needed for a trust-based explainability framework? | 17-21 |

Mapping to Design Science Research (DSR) Framework

| DSR Element | Focus | Questions |
|-------------|---|-----------|
| WHAT | Artifact = Trust-based explainability framework | 17-21 |
| WHY | Trust problems and requirements | 12-16 |
| HOW | Mechanisms for explainability and trust | 17-20 |
| LEARNING | Insights for future PMIS design | 22 |

Interviews were conducted via Zoom and in person, lasting 40-60 minutes from February to March 2026.

Table A1. Interview Details

| Code | Role | Interview Date | Duration | Mode | Language |
|------|---|----------------|----------|-----------|----------|
| PM01 | Construction PM - EPCM | 05.02.2026 | 52 min | In person | English |
| PM02 | Senior Design & Construction Manager | 15.03.2026 | 55 min | Zoom | Finnish |
| PM03 | Construction PM - Industrial | 17.03.2026 | 45 min | In person | English |
| PM04 | Construction PM | 19.03.2026 | 40 min | Zoom | English |
| PM05 | Senior Project Planner - Infrastructure | 22.03.2026 | 55 min | Zoom | English |
| PM06 | Construction PM - Commercial & Public | 26.03.2026 | 40 min | Zoom | Finnish |
| PM07 | Construction PM | 28.03.2026 | 50 min | Zoom | English |
| PM08 | Construction PM - Industrial | 28.03.2026 | 60 min | Zoom | English |
| PM09 | Construction PM - Residential | 29.03.2026 | 50 min | Zoom | English |
| PM10 | Construction PM - Construction Tech | 29.03.2026 | 60 min | Zoom | English |

Appendix 2. Microsoft 365 Copilot Prompt and Response

This appendix consists of the full prompt response from Microsoft 365 Copilot. It was used to support the researcher's own ideas for future research.

Date: April 2026

Tool used: Microsoft 365 Copilot

The Prompt

"Please read and understand the summary of my master's thesis research.

Thiess summary:

Title: A Trust-Based Framework for Explainable AI in Project Management Information Systems in Construction Industry

Research Problem:

Project managers cannot trust AI recommendations in Project Management Information Systems (PMIS) due to lack of transparency, explainability, and accountability. There is no structured, user-centered framework connecting trust theory and explainability design for AI-enabled PMIS in construction.

Research Questions:

- RQ1: How do project managers perceive trustworthiness in AI-enabled PMIS?*
- RQ2: What role does explainability play in building trust in AI-enabled PMIS?*
- RQ3: What user requirements are needed for a trust-based explainability framework for AI-enabled PMIS?*

Methodology:

- Qualitative study with 10 semi-structured interviews
- Participants: Experienced construction project managers in Finland
- Data analysis: Thematic analysis using NVivo 15 software
- using Stimulus-Organism-Response (SOR) framework

Key Findings (7 Themes):

1. Trust Factors : effective factors are transparency, track record, and alignment with site experience.
2. Distrust Triggers : black-box outputs, conflict with site reality , past inaccuracies (errors leading to financial or schedule consequences), over-precision, and missing context (ignoring stakeholder pressures, political issues).
3. Explainability Preferences: Construction managers want layered explanations including key drivers, confidence scores, visual explanations and comparable cases (similar past projects).
4. Accountability Perceptions: Project managers accept their responsibility for decisions but recognize shared accountability with organizations and other stakeholders. Every participant agreed that PMs remain accountable.
5. AI Benefits : AI provides early warning, efficiency, better decisions and resource optimization.
6. Implementation Barriers: Data quality and integration issues (systems not working together) are the biggest challenges for AI adoption. Skills gap and cost for small firms were also mentioned.
7. Human-AI Collaboration: Project managers want AI as a supporting tool (counselor or mentor) while keeping final decision authority.

One key finding:

"Site reality gap" - Even when an AI recommendation is analytically sound, it can be rejected by project managers if it ignores what is actually happening on site, such as subcontractor delays, weather conditions, access problems, or stakeholder expectations.

Proposed Framework:

A trust-based explainability framework with five layers:

- Layer 1: AI Capability (analytical functions: forecasting, risk prediction, scheduling)
- Layer 2: Explainability (key drivers, confidence scores, visual explanations, drill-down, comparable cases)
- Layer 3: Contextual Alignment (site reality integration, project constraints, stakeholder expectations)
- Layer 4: Accountability and Governance (audit trails, documentation, defensible reasoning)
- Layer 5: Human-AI Collaboration (human override, collaborative decision-making, manager final say)

my own FUTURE RESEARCH SUGGESTIONS (do not repeat these)

1. Test in different industries. This study was limited to construction industry. Would this framework work in Infrastructure, energy, manufacturing, IT projects? Future research may find the answer.

2. *Quantitative Study.* This could be a quantitative study as well. The framework can have some measurable variables. Researchers could then test how explanation quality influences trust calibration, reliance behavior, and performance outcomes with quantitative metrics and achieve numerical outcomes.
 3. *Build a prototype.* A prototype can be built in a real PMIS environment. It can be evaluated by user testing, simulations.
 4. *Compare stakeholder groups.* Different groups may have different explainability needs. Project managers, PMOs, clients, contractors, and suppliers may need different kinds of explanations.
 5. *Governance.* There might be some challenges regarding organizational policies, regulations, city laws and AI privacy concerns. All these factors affect the adoption of explainable AI in PMIS. This area is quite unexplored.
 6. *Tracking the change in trust definition.* Trust definitions may change over time when project managers gain more experience with adapting to AI systems. Future research may need to track how the same users over time could behave when trust in AI enabled PMIS evolves with repeated exposure to its recommendations.
- Based on this complete understanding of my research, please provide 10 specific, actionable suggestions for future research that are NOT already on my list above. Add a short explanation why they matter and list them clearly with numbers. "*

The Response

" Here are 10 specific, actionable suggestions for future research based on your thesis, none of which duplicate your existing six suggestions.

1. Investigate the "site reality gap" as a formal feedback loop mechanism
Why it matters: Your finding shows that even analytically sound AI fails if it ignores on-site realities. Future research could design and test a feedback loop where site managers can flag reality gaps (e.g., weather, access issues) and the system updates its recommendations in real time. This would turn a rejection trigger into a learning feature.

2. Develop and validate a "trust calibration" metric specific to construction PMIS
Why it matters: Project managers either over-trust or under-trust AI. A domain-specific metric (e.g., measuring alignment between perceived and actual AI accuracy under site constraints) would allow researchers to empirically test when trust is appropriately placed versus misplaced.

3. Examine the effect of explanation timing (pre-decision vs. post-decision) on trust

Why it matters: Your framework focuses on what explanations are given, but not when. Future research could compare whether showing explanations before a recommendation (pre-decision) versus after the manager makes a choice (post-decision) changes trust, accountability acceptance, or decision revision behavior.

4. Study the role of confidence score presentation formats (numeric, verbal, visual) on reliance behavior

Why it matters: You identified confidence scores as an explainability preference, but not how to present them. A discrete experiment could test whether "85% confidence" vs. "high confidence" vs. a color-coded bar leads to different rates of human override, especially when site reality conflicts with AI output.

5. Map how distrust triggers accumulate over consecutive AI recommendations

Why it matters: Your participants mentioned past inaccuracies as a distrust trigger, but trust erosion may not be linear. Future longitudinal research could model whether one major error (e.g., cost overrun prediction failure) does more damage than several small errors, and whether recovery is possible.

6. Investigate the “explanation burden” trade-off: more detail vs. cognitive load

Why it matters: Layered explanations (drivers, visuals, comparable cases) risk overwhelming managers in time-sensitive site decisions. Future research could identify which explanation layers are essential under high time pressure versus strategic planning contexts, preventing interface bloat.

7. Examine how organizational hierarchy moderates acceptance of AI recommendations

Why it matters: Your findings show managers keep final authority, but in construction, site managers report to PMOs or clients. Future research could study whether an AI recommendation that contradicts a superior’s opinion is rejected more often, and how explainability can mediate upward accountability.

8. Cultural and National Differences in Trust Toward AI in PMIS

Why it matters: Examine how trust perceptions differ across countries or cultural contexts (e.g., Nordic vs. Asian vs. Middle Eastern construction industries). Trust is culturally shaped; global PMIS vendors need culturally adaptive explainability strategies.

9. Quantify the cost of distrust: delayed decisions, rework, and manual overrides

Why it matters: Your framework is user-centered, but organizations adopt AI to save money. Future research could measure how distrust-driven overrides (ignoring correct AI advice) increase project costs or duration, providing a business case for implementing your framework.

10. Integration of Emotion and Intuition in Trust Models

Why it matters: Investigate how emotional factors (stress, risk aversion, past trauma from project failures) influence trust in AI recommendations. Your interviews show PMs rely heavily on intuition—understanding emotional trust drivers can improve AI design.