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How AI influences project risk perception and decision-making in international project environments

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Abstract

This thesis examines how project managers in international organisations perceive and utilise AI-supported tools in risk-related decision-making processes within international projects. The study focuses on the relationship between risk perception, organisational context, and the practical use of artificial intelligence in complex and uncertain project environments. While AI technologies are increasingly discussed as transformative tools within project management, limited research has explored how project managers actually use and interpret these systems in practice, particularly in international settings.

The study adopts a qualitative research approach based on semi-structured interviews with ten project professionals working in international project environments across different industries and organisational contexts. The collected data was analysed using a three-level thematic coding process, allowing the study to identify recurring patterns related to risk perception, organisational influence, AI usage, and decision-making practices.

The findings show that risk perception in international projects is strongly shaped by contextual, organisational, and relational factors rather than purely technical assessments of probability and impact. Communication challenges, stakeholder dynamics, organisational structures, and international complexity were identified as central influences on how risk is interpreted and managed. The study further found that AI-supported tools are currently used mainly for administrative support, information processing, analytical assistance, and pattern recognition rather than as autonomous decision-making systems.

A central conclusion of the thesis is that human judgement remains fundamental to project risk management despite the growing use of AI-supported technologies. While AI can support efficiency and analytical processes, the interpretation of uncertainty and contextual complexity continues to depend primarily on project managers themselves. The thesis therefore argues that AI currently functions most effectively as a complementary support mechanism that augments rather than replaces human decision-making in international project environments.

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1 Introduction

1.1 Background and Context

Traditional approaches to project risk management are based on structured processes designed to identify, analyse, and mitigate potential risks. In practice, organisations rely on formal tools such as risk registers, probability assessments, and contingency plans to reduce uncertainty and improve project outcomes (Veiga & Silva, 2020). These approaches assume that risk can be systematically identified and managed through rational analysis, leading to improved performance.

However, managing risk in real project environments is often less straightforward. Risk management does not take place independently of the people and organisations involved. Project managers do not simply apply formal tools in a mechanical way but interpret risks, prioritise them, and make decisions based on experience and organisational context. Research shows that the value of risk management depends on how it is applied and understood in practice, rather than on the tools alone (Willumsen et al., 2019). As a result, the way risk is managed can vary across projects and organisations. This challenge becomes more pronounced in international project environments. Projects that operate across countries and organisational boundaries are exposed to additional layers of uncertainty, including differences in regulation, culture, communication, and governance structures. In such settings, formal risk management tools may provide structure, but they do not remove ambiguity. Managers are still required to interpret incomplete information and respond to risks that are not always clearly defined.

At the same time, organisations are increasingly adopting digital technologies to support decision making. Artificial intelligence is being introduced into project management processes to improve the identification and assessment of risks. These tools can analyse large amounts of data, detect patterns, and provide predictive insights that were previously difficult to obtain (Siddiqui & Wasif, 2025). This suggests that risk management may become more data-driven and potentially more consistent across projects.

Despite these developments, the use of AI does not eliminate the role of human judgment. Project managers still need to interpret the outputs generated by these systems and decide how to act on them. Research indicates that the effectiveness of AI tools depends on how they are understood, trusted, and integrated into organisational processes (Hashimzai & Mohammadi, 2023; Fridgeirsson et al., 2023). In complex and uncertain environments, especially in international projects, this creates a new challenge, as different organisational and cultural contexts may influence how AI-based insights are used in practice. This raises an important issue. While AI has the potential to improve risk management, its effectiveness depends on how it is interpreted and applied by managers in real project environments. Understanding this interaction between technological tools and managerial judgement is therefore essential, particularly in international contexts where uncertainty is already high. For this reason, this thesis examines how project managers in international companies perceive and utilise AI-based tools in supporting risk management processes.

1.2 Problem Area and Research Gap

Although risk management is a central component of project success, there are important limitations in how it is understood and applied in practice. Traditional approaches rely heavily on structured tools and formal procedures, such as risk registers and probability-based assessments, which assume that risk can be objectively identified and managed (Veiga & Silva, 2020). While these tools provide useful structure, they offer only a partial view of how risk is actually handled in complex project environments.

In practice, risk management is not purely technical. It is shaped by how managers interpret uncertainty, prioritise threats, and make decisions within specific organisational contexts. Research shows that risk is influenced by perception, experience, and organisational factors, meaning that different managers may respond to the same situation in different ways (Willumsen et al., 2019; Christoffersen, 2023). As a result, the effectiveness of risk management depends not only on formal tools but also on managerial judgement and interpretation.

These challenges become more significant in international project environments. Projects that span multiple countries and organisations are exposed to diverse regulatory systems, cultural differences, and varying governance structures. This increases uncertainty and creates differences in how risks are understood and managed. What is considered a critical risk in one context may not be perceived in the same way in another. This highlights the need to better understand how risk management is shaped by context rather than assuming a universal approach.

At the same time, organisations are increasingly turning to artificial intelligence to support project risk management. AI tools offer the ability to analyse large datasets, identify patterns, and generate predictive insights, which can potentially improve the accuracy and efficiency of risk identification (Siddiqui & Wasif, 2025; Hashimzai & Mohammadi, 2023). From a technical perspective, these developments suggest that risk management could become more data-driven and less reliant on subjective judgement.

However, this expectation creates a new problem. The effectiveness of AI does not depend only on its technical capabilities, but on how it is used by managers in real organisational settings. Existing research largely focuses on the performance and potential of AI systems, while paying less attention to how managers perceive, trust, and integrate these tools into their decision-making processes (Fridgeirsson et al., 2023; Adamantiadou & Tsironis, 2025). Even when AI provides valuable insights, these may be ignored, misunderstood, or selectively applied depending on managerial judgement and organisational context.

This issue is particularly important in international projects, where complexity and uncertainty are already high. Differences in organisational structures, cultural norms, and decision-making practices may influence how AI tools are adopted and used. As a result, the same technology may lead to different outcomes across organisations and contexts. Despite this, the interaction

between AI, managerial perception, and international project environments remains insufficiently explored in the literature.

This leads to a clear research gap. While risk management, risk perception, and AI have each been studied extensively, there is limited understanding of how they interact in practice. In particular, little is known about how project managers in international organisations perceive and utilise AI-based tools when managing risk.

Addressing this gap is important for both theory and practice. From a theoretical perspective, it contributes to a more integrated understanding of risk management that combines technological, behavioural, and contextual factors. From a practical perspective, it helps organisations better understand how AI can be effectively integrated into project risk management processes. For these reasons, this thesis examines how project managers in international companies perceive and utilise AI-based tools in supporting risk management processes.

1.3 Research Questions

Building on the research problem, this thesis addresses the following central research question:

How do project managers in international organisations perceive and utilise AI-supported tools in risk-related decision-making processes within international projects?

This question focuses on both the interpretive and practical aspects of project risk management. It reflects the central argument of the thesis that risk perception and the use of AI-supported tools are closely connected, particularly in complex international project environments where uncertainty is shaped by organisational structures, communication processes, stakeholder relationships, and contextual conditions.

To provide further structure, the study is guided by three sub-questions. The first sub-question explores **how project managers perceive and interpret risk within international projects**. Since the findings show that risk is shaped by experience, organisational context, international complexity, and communication dynamics, understanding these perceptions is essential for analysing how risk-related decisions are made in practice.

The second sub-question examines **how AI-supported tools are utilised in project risk-related decision-making processes**. This includes how managers use these tools for tasks such as information processing, drafting, research, forecasting, pattern recognition, and analytical support. It also considers how AI-generated insights are interpreted, validated, and incorporated into existing managerial practices. While AI offers useful analytical and efficiency-related support, its actual role depends on how project managers understand, trust, and apply its outputs.

The third sub-question focuses on **which factors influence the adoption and use of AI-supported tools in international project environments**. These include trust, data quality, transparency, organisational policies, technological maturity, managerial experience, and the

specific challenges associated with international and cross-organisational projects. Exploring these factors helps explain why AI tools are used differently across contexts and why their role remains supportive rather than autonomous.

Together, the main research question and sub-questions provide a coherent framework for the study. They reflect the thesis's focus on meaning, interpretation, organisational context, and human judgement, while also allowing for an abductive exploration of how theory and empirical insights developed throughout the research process.

1.4 Scope and Delimitations

This study focuses on how project managers in international organisations perceive and utilise AI-based tools in the context of risk management. The scope is limited to project environments that involve cross-border operations, where complexity arises from differences in organisational structures, cultural contexts, and regulatory conditions. By concentrating on international projects, the study aims to capture settings in which uncertainty and variation are particularly pronounced.

The research adopts a managerial perspective, specifically examining the experiences and interpretations of project managers. It does not aim to provide a technical evaluation of AI systems or to assess the performance of specific algorithms. Instead, the focus is on how these tools are understood and applied in practice, and how they influence decision-making processes related to risk.

In terms of technology, the study considers AI-based tools broadly, including applications such as predictive analytics, machine learning models, and decision-support systems. However, it does not examine the technical design, development, or accuracy of these systems in detail. The emphasis remains on their role within organisational and managerial contexts.

Several delimitations are also applied. The study does not aim to produce generalisable findings across all industries or organisational types. Instead, it seeks to generate in-depth insights that are context-dependent and exploratory in nature. The research is further limited by its qualitative approach, which prioritises depth of understanding over breadth of coverage. As a result, the findings should be interpreted as indicative rather than universally representative.

Additionally, the study focuses on the perceptions and reported practices of project managers, rather than directly observing organisational processes or measuring project outcomes. This means that the analysis is based on subjective accounts, which may be influenced by individual experiences and organisational contexts. However, this focus is consistent with the aim of understanding how risk and AI are interpreted in practice.

Overall, these scope boundaries and delimitations ensure that the study remains focused on its central objective while acknowledging the limits of its applicability. By narrowing the focus to managerial interpretation within international project settings, the research is able to provide a more detailed and contextually grounded understanding of AI-supported risk management.

2 Literature Review

2.1 Risk and Risk Management in Projects

2.1.1 Conceptual Foundations: Definitions of Risk and the Distinction Between Risk and Uncertainty

Risk is one of the most widely used concepts in management research, yet it remains conceptually complex and theoretically contested. Across disciplines such as economics, engineering, finance, and project management, risk has been defined in different ways depending on underlying assumptions about uncertainty, knowledge, and decision-making. Understanding these differences is essential for situating risk management in international project environments.

One of the most influential formal definitions of risk is provided by Kaplan and Garrick (1981), who describe risk as a structured combination of three elements: a set of possible scenarios, the probability associated with each scenario, and the consequences that follow. In this formulation, risk becomes something that can be analytically decomposed and, at least in principle, quantified. This approach has strongly shaped technical and engineering-based risk analysis, where risk assessment relies on probability calculations and expected outcomes.

However, later research has questioned whether risk can always be reduced to quantifiable components. Aven and Renn (2010) argue that risk should not be understood merely as probability multiplied by consequence, but as a broader representation of uncertain future events, including the knowledge basis underlying assessments. They stress that risk is inherently linked to assumptions, data quality, and the limits of available knowledge. In this sense, risk is not purely objective, but partly dependent on how uncertainty is framed and interpreted.

Aven (2016) further develops this argument by examining the foundations of risk assessment and management. He shows that definitions of risk influence methodological choices and managerial practices. When risk is defined narrowly in statistical terms, organisations tend to adopt formal modelling and quantification tools. When it is defined more broadly to include ambiguity and knowledge gaps, attention shifts toward judgement, communication, and contextual interpretation. This broader perspective aligns with contemporary understandings of risk governance.

Renn (2008) contributes a governance-oriented perspective by emphasising that risk is not only a technical issue but also a social and institutional one. According to Renn, risk involves both factual assessments and value-based judgements. Different stakeholders may evaluate the same risk differently depending on their interests, cultural background, and perception of consequences. Risk therefore emerges through processes of communication and negotiation. This view is particularly relevant for international business contexts, where projects operate across cultural and regulatory environments that shape how risk is understood.

International standards such as ISO 31000 reflect this broader understanding. ISO defines risk as the effect of uncertainty on objectives, explicitly recognising that risk may involve both negative and positive outcomes. This definition moves away from a purely threat-based view and instead emphasises the relationship between uncertainty and organisational goals. It also acknowledges that uncertainty cannot always be fully quantified, reinforcing the idea that risk is partly constructed through interpretation.

The distinction between risk and uncertainty further deepens this conceptual debate. Knight (1921) provided the classical differentiation between measurable and unmeasurable uncertainty. He argued that risk refers to situations where probabilities can be assigned to outcomes, whereas true uncertainty exists when such probabilities are unknown or unknowable. This distinction remains foundational in economic and management theory and continues to influence how organisations conceptualise exposure.

In project management research, Miller and Lessard (2001) demonstrate that large and complex projects are rarely exposed only to measurable risks. Instead, they face institutional, political, technological, and market uncertainties that cannot easily be expressed in probabilistic terms. Their work suggests that traditional risk tools may be insufficient when projects operate in dynamic and evolving environments.

Chapman and Ward (2003) build on this argument by proposing a shift from project risk management toward project uncertainty management. They argue that conventional frameworks tend to focus on identifiable risk events, often captured in registers and matrices. However, many project challenges arise from ambiguity, incomplete information, and changing conditions rather than clearly defined events. By broadening the focus to uncertainty, they encourage a more holistic understanding of exposure.

Aven (2015) reinforces this critique by discussing the concept of surprise and rare, high-impact events. He highlights the limitations of probability-based models in dealing with unexpected developments that fall outside historical data. Such events challenge the assumption that future outcomes can be reliably predicted based on past experience.

Together, these perspectives reveal that risk is not a singular or universally agreed concept. It can be understood as a measurable probability distribution, as a knowledge-based assessment of uncertain futures, or as a socially embedded construct shaped by governance processes and stakeholder interpretations. Similarly, the distinction between risk and uncertainty shows that some project exposures can be analysed through statistical tools, while others require judgement and adaptive management.

These foundational debates are not merely theoretical. They influence how organisations design risk management systems, how managers interpret threats and opportunities, and how decisions are made under uncertainty. In international project environments, where complexity and ambiguity are often amplified, the conceptual framing of risk becomes particularly significant. Understanding these theoretical foundations therefore provides an essential basis

for examining how project managers perceive and utilise tools, including AI-based systems, in their risk management practices.

2.1.2 Traditional Project Risk Management Frameworks and Their Practical Application

Building on the conceptual foundations of risk and uncertainty, project management research has developed structured frameworks designed to identify, assess, and control risk in practice. These frameworks aim to transform abstract uncertainty into manageable categories and procedures. Over time, they have become institutionalised in standards, professional guidelines, and organisational routines.

Traditional project risk management frameworks generally follow a linear and process-oriented logic. Risk management is treated as a sequence of steps that begins with planning and identification, continues with qualitative and quantitative assessment, and concludes with response planning and monitoring. Hillson and Simon (2020) describe this structured approach as central to professional project risk practice, emphasising that systematic processes provide clarity and accountability. Their work illustrates how formal frameworks attempt to integrate risk thinking into overall project governance.

Empirical research has examined the effectiveness of such frameworks. Raz, Shapiro, and Globerson (2002) show that formal risk management practices are associated with improved project performance, particularly when risk analysis is integrated into early planning stages. Similarly, Zwikael and Ahn (2011) demonstrate that systematic risk planning contributes positively to project outcomes across industries. Their findings suggest that structured frameworks can enhance predictability and preparedness when implemented consistently.

However, these frameworks are not uniform across organisations. Hillson (2004) expands the traditional threat-based focus of risk management to include opportunity management, arguing that projects should also actively manage positive risk. This extension reflects an evolving understanding that risk management should not only aim to minimise negative outcomes but also to exploit potential advantages. Oehmen, Seidel, and Rebentisch (2014) further position risk management within a broader value-oriented perspective, suggesting that risk processes should support resilience and strategic flexibility rather than mere compliance.

Despite these variations, most traditional frameworks share common procedural elements. These elements are clearly articulated in the Project Management Institute's PMBOK Guide (PMI, 2021), which has become one of the most influential standards in global project management practice. The PMBOK framework defines project risk management as a structured set of processes that includes planning risk management, identifying risks, performing qualitative and quantitative risk analysis, planning risk responses, implementing responses, and monitoring risks.

The PMBOK perspective treats risk as an event or condition that, if it occurs, may have a positive or negative effect on project objectives. This definition aligns with ISO 31000 and reflects the broader understanding of risk as linked to uncertainty and objectives. However,

PMBOK operationalises this definition through formal tools and documentation procedures. Risk registers, probability-impact matrices, and response plans are central instruments in this process. The logic is procedural and systematic, aiming to ensure that risks are identified early and addressed proactively.

The PMI Practice Standard for Project Risk Management (2019) further elaborates these processes and provides detailed guidance on techniques for risk identification and analysis. Techniques such as brainstorming, expert interviews, checklists, and historical data review are commonly used during the identification phase. During assessment, qualitative analysis often precedes quantitative modelling, especially when numerical data are limited. Risk mitigation strategies typically involve avoidance, transfer, mitigation, or acceptance.

Comparative analyses of PMBOK and other standards reinforce the structured and process-driven nature of this approach. Vargas (2019) highlights that PMBOK emphasises documentation and traceability, ensuring that risks are systematically recorded and monitored. Tolani (2019) similarly notes that PMBOK focuses strongly on procedural clarity and role definition, which contributes to standardisation across organisations. Hillson and Murray-Webster (2017) add that while the PMBOK framework is comprehensive, it tends to assume a rational decision-making model in which managers evaluate risk objectively based on available information.

The core operational elements of risk management are identification, assessment, and mitigation. Chapman and Ward (2003) provide an in-depth discussion of these processes, arguing that risk identification is often the most critical yet most challenging step. If important uncertainties are not identified early, subsequent analysis becomes incomplete. Loosemore, Raftery, Reilly, and Higgon (2015) similarly emphasise that identification relies heavily on managerial judgement and organisational culture, despite the presence of formal tools.

Risk assessment typically involves evaluating both likelihood and impact. Bannerman (2008), in his reassessment of risk management in software projects, observes that while formal assessment techniques are widely used, their application often depends on subjective estimation rather than purely statistical data. Zwikael and Meredith (2018) further demonstrate that the effectiveness of risk mitigation depends not only on technical analysis but also on organisational commitment and communication.

Taken together, traditional project risk management frameworks present risk as something that can be systematically categorised, analysed, and controlled through structured processes. They offer practical tools that aim to increase transparency and predictability. At the same time, empirical research indicates that the application of these frameworks depends significantly on human judgement, organisational context, and managerial interpretation.

This tension between formal structure and practical interpretation forms an important transition toward the next section, which critically examines the rational assumptions embedded in traditional risk models.

2.1.3 Cognitive bias in Risk Management Frameworks

Although traditional project risk management frameworks offer structured ways to identify and analyse risk, many researchers have questioned the assumptions behind these approaches. In particular, the idea that risk can be fully understood through rational calculation and objective analysis has been widely challenged. In practice, risk is rarely that clear or measurable.

Much of the literature points out that probability-based models often simplify complex situations, making them easier to analyse but less reflective of reality. In addition, decision making is not purely rational, as managers are influenced by cognitive biases, past experiences, and organisational pressures. Risk management therefore takes place within a broader social and organisational context, rather than as a purely technical exercise.

One of the most influential critiques comes from behavioural decision theory. Kahneman and Tversky (1979), through the development of prospect theory, demonstrated that individuals do not evaluate risk in the purely rational way assumed by classical economic models. Their research showed that decision makers often rely on heuristics and mental shortcuts when assessing uncertain outcomes. As a result, perceptions of risk are shaped by psychological factors such as loss aversion, framing effects, and reference points. These findings suggest that managerial risk evaluation may deviate significantly from formal probabilistic logic.

This behavioural perspective is reinforced in organisational studies. March and Shapira (1987) examined how managers interpret risk within real decision-making environments and found that managerial perceptions often differ from technical definitions. Rather than focusing on statistical probabilities, managers tend to concentrate on performance thresholds, organisational survival, and the potential consequences of failure. Risk therefore becomes linked to strategic considerations and organisational priorities rather than simply to measurable uncertainty.

In project management research, similar critiques have emerged. Flyvbjerg (2014) argues that large infrastructure and organisational projects frequently suffer from systematic underestimation of risk due to optimism bias and strategic misrepresentation. Project planners and decision makers may present overly optimistic projections in order to secure project approval or funding. This behaviour undermines the assumption that risk assessments represent neutral and objective evaluations.

Other scholars have criticised the institutional role of formal risk management systems. Power (2007) suggests that risk management frameworks can sometimes create an illusion of control. Organisations may adopt extensive risk documentation and reporting systems that signal responsibility and compliance, yet these systems do not necessarily improve the ability to anticipate or manage uncertainty. In this sense, risk management may function partly as a symbolic practice that legitimises organisational decisions rather than a purely analytical process.

The complexity of modern organisational environments further challenges the assumptions of rational risk models. Weick and Sutcliffe (2007), drawing on research on high reliability organisations, argue that uncertainty in complex systems often exceeds the predictive capabilities of formal analysis. Instead of relying solely on prediction and control, organisations must develop processes of sensemaking that allow managers to interpret evolving situations and respond to unexpected developments.

Taleb (2007) provides an additional critique by highlighting the role of rare and extreme events. According to Taleb, traditional statistical models rely heavily on historical data and normal probability distributions, which often fail to account for highly improbable but high-impact events. These so-called black swan events demonstrate the limits of probabilistic forecasting and reveal how organisations may underestimate exposure to unexpected disruptions.

A broader sociological critique is offered by Beck (1992), who argues that modern societies increasingly produce systemic risks that cannot be fully calculated or contained. Technological complexity, global interdependence, and institutional uncertainty create conditions in which risk is both pervasive and difficult to predict. From this perspective, risk becomes a social phenomenon shaped by institutional structures and collective interpretations.

Within the field of project management, Geraldi, Maylor, and Williams (2011) extend these arguments by examining the complexity inherent in many project environments. Their work shows that projects often involve dynamic interactions among multiple stakeholders, technologies, and institutional settings. In such contexts, linear risk models may oversimplify the nature of uncertainty. Instead, project managers must navigate ambiguous information and evolving conditions, relying on interpretation and experience as much as formal analysis.

These critiques do not suggest that traditional risk management frameworks are without value. Structured processes such as those described in the PMBOK framework provide useful tools for organising information and facilitating communication. However, the literature increasingly emphasises that risk management cannot rely solely on rational calculation. Cognitive biases, organisational incentives, institutional pressures, and environmental complexity all influence how risks are perceived and addressed.

Understanding these limitations is particularly important when examining contemporary developments such as the integration of artificial intelligence into project management processes. AI-based systems are often promoted as tools capable of improving predictive accuracy and supporting data-driven decision making. However, if risk perception and evaluation are shaped by social and organisational factors, the effectiveness of such technologies will depend not only on their technical capabilities but also on how managers interpret and utilise them in practice.

For this reason, the following sections of the literature review move beyond technical risk frameworks and focus on the role of managerial perception, organisational sensemaking, and international context in shaping risk management practices.

2.2 Traditional perceptions of risk

2.2.1 Risk Perception and Managerial Interpretation of Risk

While traditional project risk management frameworks often treat risk as an objective and quantifiable phenomenon, research has increasingly emphasised that risk is also a matter of human perception and interpretation. Risk perception theory examines how individuals understand, evaluate, and respond to uncertain events, highlighting the influence of psychological, social, and cultural factors in shaping judgements. This perspective is particularly relevant in complex project environments, where managers must make decisions under incomplete information and evolving conditions.

One of the foundational contributions to risk perception research comes from Slovic (1987), who demonstrated that individuals do not assess risks purely based on statistical probabilities. Instead, qualitative characteristics such as perceived severity, familiarity, and controllability strongly influence judgement. Risks perceived as unfamiliar, uncontrollable, or catastrophic are often judged as more threatening, even when their actual likelihood is low. These findings suggest that risk evaluation depends not only on measurable probability but also on how uncertainty is experienced and interpreted.

Cultural and social factors further shape risk perception. Douglas and Wildavsky (1982) argue that different social groups interpret risks according to their shared values and organisational norms. Their cultural theory of risk highlights that perceptions of threat reflect underlying beliefs about authority, responsibility, and acceptable behaviour. In organisational settings, managers' perceptions are also shaped by professional experience, decision-making responsibilities, and organisational culture (Sitkin & Weingart, 1995). Thus, risk perception is inherently context-dependent and cannot be understood in isolation from the environment in which it occurs.

Project management research demonstrates that risk perception significantly affects decision making. Weber, Blais, and Betz (2002) show that individuals vary in their risk attitudes, meaning that managers may interpret the same project scenario in different ways. These differences influence which risks are prioritised, which mitigation strategies are adopted, and how much confidence is placed in formal analyses. In international projects, where complexity and ambiguity are amplified by cross-cultural and institutional differences, understanding managerial risk perception becomes even more critical.

Closely related to risk perception is the study of cognitive biases systematic patterns in human judgement that arise from mental shortcuts or heuristics used to process complex information. Kahneman and Tversky (1979) identified several key biases that affect risk evaluation. The availability heuristic leads individuals to judge the probability of events based on how easily similar examples come to mind, often exaggerating the perceived likelihood of dramatic or memorable events. Overconfidence, another common bias, causes decision makers to overestimate their knowledge or predictive ability, which can result in underestimation of

potential risks. Optimism bias is particularly salient in project contexts, where planners may underestimate costs, timelines, and challenges due to both psychological tendencies and organisational incentives (Flyvbjerg, 2014).

These cognitive tendencies indicate that risk evaluation cannot be understood purely as a rational or objective process. Even when managers have access to structured tools, quantitative data, or formal frameworks, their interpretation of risk is filtered through individual cognition, experience, and judgement. Research suggests that biases cannot be fully eliminated through procedural measures alone, because risk management is ultimately enacted by human agents operating within organisational structures.

The interaction between risk perception and cognitive bias has practical implications for risk management. It explains why managers may prioritise certain risks over others, even when analytical models suggest a different focus. It also underscores the importance of combining formal risk assessment with interpretive processes such as discussion, sensemaking, and judgement. In complex projects, particularly international ones, these human elements determine how risk information is interpreted, communicated, and acted upon.

Finally, these insights are crucial for understanding how emerging technologies, including artificial intelligence, are integrated into project risk management. AI tools may provide predictive analytics, probability estimates, and scenario modelling, but their effectiveness depends on managerial interpretation. If risk perception and cognitive biases shape which outputs are trusted and acted upon, AI cannot replace human judgement but must instead be seen as augmenting it. Understanding these dynamics is essential for evaluating the potential of AI to support risk management in international projects, where ambiguity, uncertainty, and stakeholder diversity are heightened.

2.2.2 Behavioural Decision Theory and Organisational Sensemaking

While risk perception theory highlights how individuals interpret uncertain situations, behavioural decision theory provides a broader framework for understanding how decision makers evaluate risk and make choices under uncertainty. In contrast to traditional rational decision models, behavioural decision theory assumes that individuals operate with limited information, cognitive constraints, and subjective interpretations. Decisions are therefore influenced not only by objective data but also by experience, intuition, and contextual factors.

One of the central ideas within behavioural decision theory is that individuals do not behave as perfectly rational actors. Instead, they rely on simplified decision rules when dealing with complex problems. March and Shapira (1987) argue that managers often evaluate risk in terms of potential gains and losses relative to organisational targets rather than through formal probability calculations. In practice, this means that managers may focus on avoiding outcomes that threaten performance expectations while being willing to accept risks that appear manageable within organisational limits.

Behavioural research also suggests that decision making is shaped by organisational routines and institutional environments. Managers rarely evaluate risks independently. Instead, they operate within organisational structures that influence which information is considered relevant and which risks are prioritised. This perspective highlights that risk evaluation is not only an individual cognitive process but also a socially embedded activity that unfolds within organisational contexts.

In project management environments, this behavioural perspective is particularly important. Projects often involve multiple stakeholders, evolving objectives, and uncertain conditions. As a result, decision makers must interpret ambiguous information and coordinate their understanding with others involved in the project. Behavioural decision theory therefore emphasises the importance of judgement, experience, and interaction in shaping how risks are evaluated and managed.

Closely connected to behavioural decision theory is the concept of organisational sensemaking. Sensemaking refers to the process through which individuals and groups interpret complex or uncertain situations and construct shared understandings that guide action. Weick (1995) describes sensemaking as an ongoing process in which actors interpret events retrospectively in order to make them meaningful within a broader organisational context.

In project environments, sensemaking plays a critical role in the interpretation of risk information. Managers rarely encounter risks as clearly defined events. Instead, potential threats emerge gradually through signals, observations, and interactions among team members. Through discussion and interpretation, project participants collectively determine whether a situation constitutes a risk and how it should be addressed.

Sensemaking processes are particularly relevant in international projects where teams often consist of members from different cultural and professional backgrounds. Differences in experience, expertise, and expectations may lead to varying interpretations of the same situation. Through communication and negotiation, project teams gradually develop shared understandings that allow them to coordinate their responses to uncertainty.

This perspective highlights that risk management is not solely a technical process of identifying and analysing risks. It is also a social process in which organisational actors interpret events, negotiate meaning, and develop collective responses. Even when formal risk management tools or analytical models are used, their outputs must still be interpreted by managers who integrate them into ongoing decision-making processes.

Understanding behavioural decision theory and organisational sensemaking is particularly important when considering the integration of new technologies into project risk management. Artificial intelligence systems may generate predictions, risk indicators, or scenario analyses, but their influence depends on how managers interpret and incorporate these outputs into their existing decision-making processes. If risk management involves sensemaking and interpretation, then AI tools become part of a broader organisational process rather than purely technical decision-support systems.

Consequently, examining how managers perceive and interpret AI-generated insights becomes essential for understanding the role of artificial intelligence in project risk management. The behavioural and sensemaking perspectives therefore provide an important conceptual foundation for analysing how project managers engage with AI-based tools when identifying and responding to risk in complex international projects.

2.2.3 Cultural Differences in Risk Perception and the International Management Perspective

Risk perception is not shaped solely by individual cognition or organisational processes. Cultural context also plays a significant role in influencing how uncertainty is interpreted and how risks are evaluated. Scholars in international management and cross-cultural research have long argued that attitudes toward uncertainty and risk vary across societies, reflecting differences in values, institutional environments, and social norms.

One of the most influential frameworks in this area is Hofstede's cultural dimensions theory. Hofstede (2001) introduced the concept of uncertainty avoidance to describe the extent to which members of a society feel uncomfortable with ambiguity and uncertain situations. Societies with high uncertainty avoidance tend to prefer structured rules, formal procedures, and clear planning in order to reduce unpredictability. In contrast, societies with lower uncertainty avoidance may be more tolerant of ambiguity and more willing to experiment with uncertain outcomes. These differences can influence how managers approach risk management, including how risks are identified, prioritised, and addressed within organisations.

Research in international business suggests that cultural values influence not only attitudes toward uncertainty but also decision-making behaviour more broadly. Weber and Hsee (1998) demonstrate that cultural context affects individuals' willingness to take risks, as well as their interpretation of potential gains and losses. Their findings indicate that individuals from different cultural backgrounds may evaluate the same uncertain situation in fundamentally different ways. As a result, risk perception cannot be assumed to be uniform across international organisations or project teams.

In the context of multinational companies and international projects, cultural differences in risk perception may influence both individual decision making and collective organisational processes. Project teams often consist of members from multiple national and professional backgrounds, each bringing their own assumptions about acceptable levels of risk and appropriate responses to uncertainty. These differences may affect how risks are discussed, how seriously certain threats are perceived, and how mitigation strategies are developed.

The international management literature highlights that managing across cultural boundaries requires sensitivity to these differences in perception and interpretation. Adler (2008) argues that managers operating in international environments must recognise that decision-making processes are shaped by diverse cultural perspectives. Rather than assuming a single rational

approach to risk management, organisations must often balance multiple interpretations of uncertainty within global teams.

Furthermore, institutional environments can also shape organisational attitudes toward risk. Differences in regulatory frameworks, industry standards, and market conditions may influence how companies approach risk management practices across countries. Firms operating internationally must therefore navigate not only cultural differences among employees but also structural differences in the environments in which projects are conducted.

These dynamics are particularly relevant in the management of international projects, where complexity is often heightened by geographical dispersion, cross-cultural communication, and diverse stakeholder expectations. In such environments, risk perception becomes a shared and negotiated process rather than a purely individual assessment. Managers must interpret signals from different contexts, reconcile varying perspectives among team members, and coordinate responses that are acceptable across organisational and cultural boundaries.

Understanding cultural differences in risk perception therefore contributes to a more comprehensive understanding of risk management in international project settings. It highlights that risk evaluation is influenced not only by analytical tools and formal frameworks but also by social, cultural, and organisational contexts.

This perspective also provides an important foundation for examining the integration of artificial intelligence into project risk management. AI-based tools may offer data-driven insights or predictive models, yet their effectiveness ultimately depends on how these outputs are interpreted by managers working within diverse organisational and cultural contexts. In international companies, differences in attitudes toward technology, trust in automated systems, and tolerance for uncertainty may further influence how AI-supported risk management practices are adopted and utilised.

Consequently, analysing risk perception from an international management perspective is essential for understanding how project managers engage with emerging technological tools in complex global environments. By recognising the influence of culture and organisational context, research can provide deeper insights into the ways managers interpret risk information and incorporate technological support into their decision-making processes.

2.3 Institutional and cultural factor influencing risk management

2.3.1 Complexity and Institutional Context in International Projects

Managing risk in international projects is particularly challenging due to the high level of complexity and the presence of different institutional environments. These factors influence not only how risks emerge, but also how they are identified and managed by project managers.

A key characteristic of international projects is their complexity. Project complexity is commonly understood as the number of elements involved in a project and the relationships

between them (Baccarini, 1996). As projects grow in size and involve more stakeholders, technologies, and activities, the number of interactions increases. This makes it more difficult to predict outcomes and identify potential risks in advance.

Research has shown that complexity is closely linked to uncertainty. Williams (1999) argues that in complex projects, it becomes harder to understand cause and effect relationships, which increases the likelihood of unexpected events. In international projects, this issue is even more pronounced. Projects often involve teams located in different countries, working across time zones and cultural contexts. Communication becomes more difficult, and misunderstandings can occur more easily, which can lead to additional risks.

In addition to structural complexity, international projects are also influenced by changing external conditions. Market environments, political situations, and regulatory frameworks may differ across countries and can change over time. Geraldi, Maylor, and Williams (2011) highlight that project complexity is not only technical but also organisational and environmental. This means that managers must deal with uncertainty that is constantly evolving, rather than something that can be fully analysed at the beginning of a project.

Alongside complexity, institutional differences play an important role in shaping risk in international projects. Institutions can be defined as the formal and informal rules that guide behaviour in a given context, including laws, regulations, and social norms (North, 1990). These institutions vary significantly across countries and influence how organisations operate.

From an international business perspective, firms must adapt their practices to fit the institutional environment in which they operate. Peng, Wang, and Jiang (2008) argue that organisational strategies are shaped not only by internal resources but also by external institutional conditions. In the context of project management, this means that risk management practices cannot always be standardised across different countries.

Institutional differences can affect risk in several ways. Legal systems may differ in terms of contract enforcement, which can create uncertainty in partnerships and agreements. Regulatory requirements may introduce additional compliance risks, especially in industries that are heavily regulated. Cultural norms can also influence how risks are perceived and communicated within project teams.

Research on multinational organisations shows that practices developed in one country are not always easily transferred to another. Kostova (1999) explains that differences in local norms and expectations can make it difficult to implement standard organisational practices across borders. As a result, project managers often need to adapt risk management approaches to fit the local context, which adds another layer of complexity.

The combination of project complexity and institutional differences creates a challenging environment for risk management. Managers must deal with multiple sources of uncertainty at the same time, including technical, organisational, and environmental factors. This makes it difficult to rely solely on standardised tools or predefined procedures.

These challenges highlight the importance of flexibility and interpretation in managing risk in international projects. While formal frameworks provide structure, they may not fully capture the dynamic and context-specific nature of risks in global environments. This creates a need for approaches that can support decision making under complexity and adapt to different institutional settings.

This discussion also provides a link to the role of emerging technologies such as artificial intelligence. AI-based tools have the potential to support risk identification and analysis in complex environments by processing large amounts of data. However, their effectiveness depends on their ability to account for contextual differences and to be interpreted correctly by managers. Understanding the complexity and institutional context of international projects is therefore essential for evaluating how such tools can be used in practice.

2.3.2 Organisational and Cultural Influences on Risk Management in International Projects

In addition to structural complexity and institutional differences, risk management in international projects is strongly influenced by organisational and cultural factors. These factors shape how decisions are made, how risks are interpreted, and how management practices are implemented across different contexts. Understanding these influences is essential for explaining why risk management practices often vary between organisations and across international environments.

Cultural influences play a central role in managerial decision making. Research in cross-cultural management shows that individuals from different cultural backgrounds may approach uncertainty, authority, and decision making in different ways. Hofstede (2001) highlights that dimensions such as uncertainty avoidance and power distance affect how individuals respond to ambiguous situations and how decisions are structured within organisations. In cultures with high uncertainty avoidance, managers may prefer formal procedures and detailed planning in order to reduce risk. In contrast, in cultures with lower uncertainty avoidance, managers may be more willing to rely on flexible approaches and accept uncertain outcomes.

These cultural differences influence not only individual decision making but also communication and coordination within project teams. In international projects, team members may interpret the same situation differently depending on their cultural background. This can affect how risks are discussed, whether concerns are openly expressed, and how quickly decisions are made. As a result, risk management becomes a process that involves negotiation and alignment between different perspectives rather than a purely technical assessment.

Beyond culture, there is also significant variation in how organisations approach risk management. Even within the same industry, firms may differ in their structures, processes, and attitudes toward risk. Some organisations rely heavily on formal frameworks and standardised procedures, while others adopt more flexible and experience-based approaches.

These differences can be linked to organisational culture, past experiences, and strategic priorities.

Research on organisational practices suggests that firms develop their own ways of managing uncertainty over time, which become embedded in routines and decision-making processes. As a result, risk management is not implemented in a uniform way across organisations. Instead, it reflects internal norms, leadership styles, and organisational learning. In international projects, where multiple organisations may collaborate, these differences can create additional challenges. Project partners may have different expectations regarding risk identification, reporting, and mitigation, which can complicate coordination and decision making.

2.3.3 How do governance structures influence risk management?

Governance structures in multinational firms further shape how risk is managed across borders. Multinational organisations often operate with a combination of centralised and decentralised control mechanisms. Headquarters may establish global standards and frameworks, while local units adapt these practices to fit their specific context. This creates a balance between standardisation and flexibility, which is particularly important in managing risk across different institutional environments (Bartlett & Ghoshal, 1989; Peng et al., 2008).

Research suggests that governance structures influence how information flows within organisations and how decisions are made. In highly centralised structures, decision making may be concentrated at higher levels of the organisation, which can support consistency but may slow down responses to local risks. In more decentralised structures, local managers may have greater autonomy to respond to emerging risks, but this can lead to variation in practices across different units.

In the context of international projects, governance structures affect how risk information is shared, how responsibilities are allocated, and how decisions are coordinated across locations. Effective risk management requires not only identifying risks but also ensuring that relevant information reaches the appropriate decision makers in a timely manner. Differences in governance can therefore influence both the efficiency and the effectiveness of risk management processes.

The transfer and implementation of risk management practices across borders is also influenced by local organisational and institutional contexts. Kostova (1999) shows that organisational practices developed at headquarters are not always adopted uniformly across subsidiaries, as local norms, values, and institutional pressures shape how these practices are interpreted and applied. This further reinforces the idea that risk management processes may vary even within the same multinational firm.

The interaction between cultural influences, organisational variation, and governance structures highlights that risk management in international projects is shaped by multiple layers of context. Managers must navigate differences in values, practices, and organisational

arrangements while responding to uncertainty. This reinforces the idea that risk management is not simply a technical activity but a socially and organisationally embedded process.

These considerations are particularly relevant when examining the adoption of new tools and technologies. Artificial intelligence systems may provide analytical insights, but their use depends on organisational practices, cultural attitudes toward technology, and governance structures that determine how decisions are made. In multinational firms, differences in these factors may influence whether AI tools are adopted, how they are used, and how their outputs are interpreted (Peng et al., 2008).

Understanding organisational and cultural influences therefore provides an important foundation for analysing how risk management practices evolve in international settings. It also helps explain why the integration of new technologies such as AI may vary across firms and contexts, setting the stage for a more focused discussion on digital and AI-based tools in project risk management.

In addition to complexity and institutional differences, risk management in international projects is also shaped by cultural and organisational factors. These factors influence how managers make decisions, how risks are interpreted, and how management practices are applied in different contexts. As a result, risk management cannot be treated as a fully standardised process, but rather as something that is shaped by the environment in which it takes place.

Cultural influences play an important role in how managers approach uncertainty and risk. Research in cross-cultural management shows that individuals from different cultural backgrounds tend to evaluate and respond to risk in different ways. Hofstede (2001) demonstrates that cultural dimensions such as uncertainty avoidance influence how comfortable individuals are with ambiguity and unclear outcomes. In high uncertainty avoidance cultures, managers often prefer structured processes, formal rules, and detailed planning. In contrast, in cultures where uncertainty is more accepted, decision making may be more flexible and adaptive.

These differences are particularly visible in international project environments. When individuals from different cultural backgrounds work together, they may not interpret risks in the same way. What one manager considers a significant threat, another may see as manageable. Research by Weber and Hsee (1998) further shows that while people across cultures may share similar general attitudes toward risk, their perceptions of specific risks can differ significantly. This can influence how risks are prioritised and how decisions are made within project teams.

In addition, cultural differences affect communication and interaction within teams. Adler (2008) points out that communication styles vary across cultures, which can influence how openly risks are discussed. In some contexts, raising concerns may be encouraged, while in others it may be avoided in order to maintain harmony. This can create challenges in identifying

and addressing risks early in international projects, as not all team members may feel equally comfortable expressing uncertainty or disagreement.

Alongside cultural influences, organisations themselves differ in how they approach risk management. Even within the same industry, firms can have very different practices, structures, and attitudes toward risk. Some organisations rely heavily on formal risk management frameworks and standardised procedures, while others depend more on managerial experience and informal judgement. March and Shapira (1987) argue that managerial perceptions of risk are often shaped by organisational context, including past experiences and internal norms, rather than purely objective assessments.

Over time, these organisational characteristics become embedded in routines and practices. As Weick (1995) explains through the concept of sensemaking, organisations interpret and respond to uncertainty based on shared understandings and past experiences. This means that risk management practices are not only technical processes but are also shaped by how organisations collectively make sense of uncertain situations. In international projects, where multiple organisations may collaborate, these differences can lead to misalignment in how risks are understood and managed.

Governance structures in multinational firms add another important dimension. Large international organisations often operate with a mix of centralised and decentralised control. Headquarters may define overall strategies and frameworks, while local units adapt these to their specific environments. Kostova (1999) highlights that organisational practices are not always transferred uniformly across borders, as local contexts influence how they are implemented.

This creates a balance between standardisation and local adaptation. On one hand, centralised governance can support consistency in risk management practices across the organisation. On the other hand, decentralised structures allow local managers to respond more effectively to context-specific risks. Peng, Wang, and Jiang (2008) argue that firms operating internationally must continuously navigate between global integration and local responsiveness, which also applies to risk management practices.

These governance differences influence how information flows within organisations and how decisions are made. In more centralised systems, decision making may be slower but more consistent, while decentralised systems may enable faster responses but lead to variation across units. As a result, risk management in multinational firms is shaped not only by formal frameworks but also by how authority and responsibility are distributed across organisational levels.

Overall, cultural influences, organisational differences, and governance structures all play a key role in shaping risk management in international projects. Managers must navigate different ways of thinking, different organisational practices, and different decision-making systems while dealing with uncertainty. This reinforces the idea that risk management is not only a technical activity but also a socially and organisationally embedded process.

These insights are particularly important when considering the introduction of new technologies such as artificial intelligence. While AI tools may offer advanced analytical capabilities, their actual use depends on organisational context. Cultural attitudes toward technology, existing practices, and governance structures will all influence how these tools are adopted and how their outputs are interpreted. Understanding these factors therefore provides an important foundation for analysing the role of AI in project risk management.

2.4 AI in project management

2.4.1 Artificial Intelligence in Project Risk Management

Artificial intelligence has increasingly become a focus in project management, particularly for supporting decision making under uncertainty. To understand its potential in risk management, it is first necessary to clarify what is meant by AI and the different types of AI technologies that are relevant in this context. Broadly, AI refers to systems that can perform tasks that typically require human intelligence, such as reasoning, learning, problem solving, and pattern recognition (Russell & Norvig, 2021). In project management, AI tools are commonly used to process large volumes of data, detect patterns, predict outcomes, and provide recommendations to decision makers.

There are several types of AI that are applicable in project management. Rule-based systems, also called expert systems, rely on predefined rules to make decisions or provide guidance. These systems are useful for structured problems where clear guidelines exist, but they are limited when situations are complex or uncertain. More advanced AI systems use machine learning, where algorithms learn from historical data to make predictions or classify information without being explicitly programmed for every scenario (Hashimzai & Mohammadi, 2023). Machine learning can identify patterns in project data, such as correlations between risk indicators and project outcomes, which may not be apparent to human managers.

Machine learning is particularly valuable in supporting decision making under uncertainty. It can analyze large datasets from previous projects, detect trends, and highlight potential risks early in the project lifecycle (Siddiqui & Wasif, 2025). For example, predictive models can estimate the probability of cost overruns, delays, or quality issues based on past performance data. This allows project managers to allocate resources more effectively, plan mitigation strategies, and monitor risks in a proactive manner. By providing data-driven insights, machine learning can complement human judgment and improve the overall quality of risk management decisions.

Another advantage of AI is its ability to continuously learn and adapt. As new data becomes available, machine learning models can update their predictions and refine their understanding of risk factors. This dynamic capability is particularly relevant in international projects, where conditions can change rapidly and managers must respond to unforeseen challenges. AI systems can process information faster than humans and provide decision support that is timely, consistent, and evidence-based.

While the potential of AI is significant, its effectiveness depends on how it is integrated into existing project management practices. Human managers still play a critical role in interpreting AI outputs, making final decisions, and considering contextual factors that may not be captured in the data (Fridgeirsson et al., 2023). In this sense, AI should be seen as a tool that enhances managerial capabilities rather than replacing human judgment. The successful use of AI in project risk management requires careful consideration of organisational practices, team expertise, and governance structures, particularly in multinational projects.

In summary, AI in project management encompasses a range of technologies, from rule-based systems to machine learning, that can support decision making and risk management. Machine learning, in particular, offers powerful capabilities for analyzing historical data, predicting potential issues, and improving the timeliness and quality of decisions. However, the integration of AI into project risk management must be carefully managed to ensure that it complements human expertise and aligns with organisational practices.

2.4.2 AI in Risk Assessment: Predictive Analytics and Decision Support

One of the most significant applications of AI in project risk management is in risk assessment, where predictive analytics can provide valuable insights to managers. Predictive analytics refers to the use of algorithms, often based on machine learning, to analyze historical and real-time project data in order to forecast potential risks and outcomes (Siddiqui & Wasif, 2025). By identifying patterns and correlations that may not be obvious to human managers, predictive analytics can help anticipate issues such as cost overruns, schedule delays, or resource shortages before they occur.

The advantage of predictive analytics lies in its ability to process large volumes of complex data quickly and systematically. Traditional risk assessment often relies on expert judgment, which can be subjective and influenced by cognitive biases. AI-based predictive models, on the other hand, provide a more objective and consistent approach, allowing managers to make data-informed decisions. For example, historical project data can be used to model the likelihood of different risk scenarios, helping managers allocate resources, plan mitigation strategies, and prioritize attention to the most critical areas (Fridgeirsson et al., 2023).

An important distinction in AI application is between automation and augmentation. Automation refers to AI systems taking over tasks that were previously performed manually, such as generating risk reports or monitoring key performance indicators in real time. Augmentation, in contrast, refers to AI supporting human decision-making without replacing it, providing recommendations, insights, or alerts that managers can interpret and act upon (Hashimzai & Mohammadi, 2023). In project risk management, augmentation is particularly valuable, as managers often need to integrate AI outputs with contextual knowledge, experience, and judgment that cannot be fully captured by algorithms.

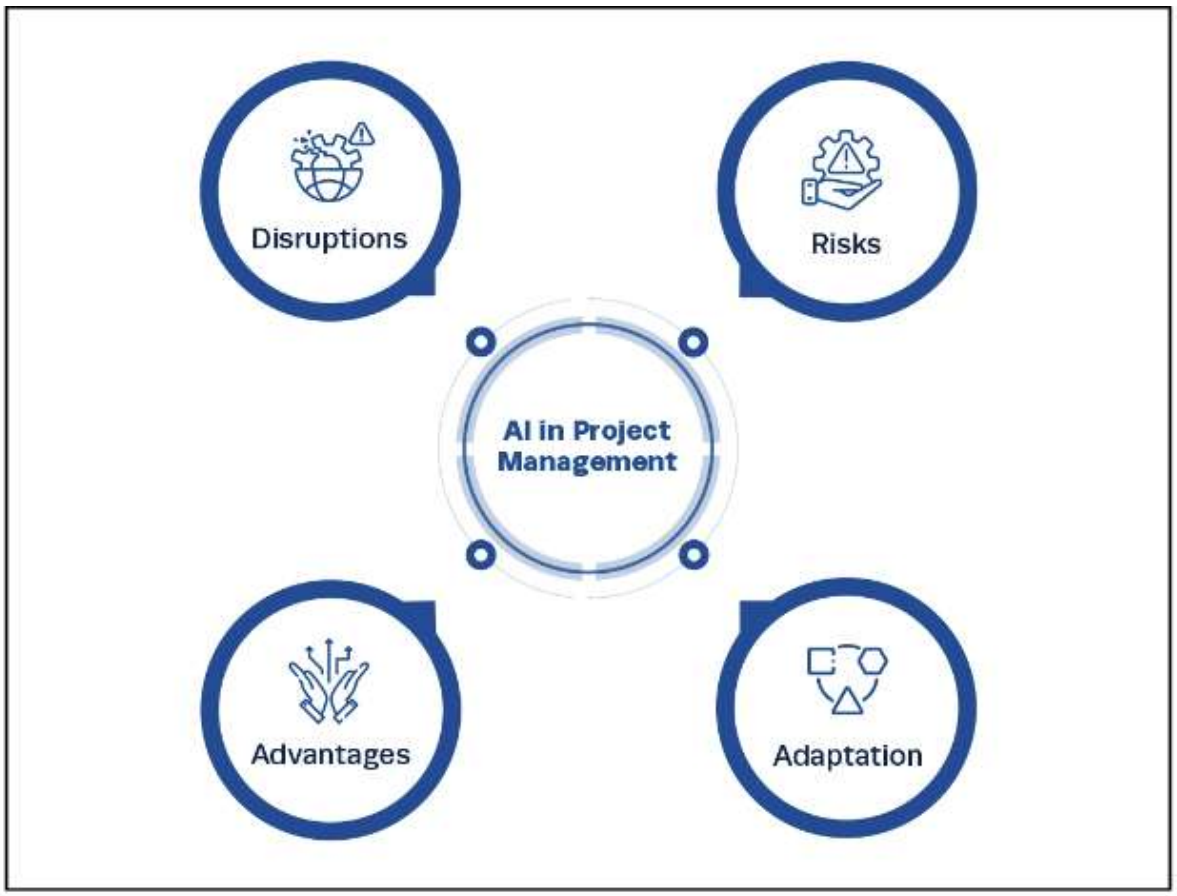

Figure 1 (Hashimzai & Mohammadi, 2023 The AI-Powered Project Management Framework,)

The AI- Powered Project Management Framework emphasizes how Artificial Intelligence (AI) can significantly influence contemporary project management by tackling essential factors such as disruptions, risks, benefits, and adaptation. AI's capability to analyze real-time data and historical patterns enables it to proactively spot potential disruptions, including supply chain complications or unexpected incidents, allowing project managers to execute contingency plans ahead of time

For instance, AI can flag a potential delay in a project milestone based on predictive patterns in historical schedules. A human manager can then evaluate the causes, consider unique project circumstances, and decide on an appropriate course of action. This combination of AI-driven insights and human expertise allows for more informed and flexible risk management decisions, particularly in complex or international projects where multiple factors interact (Siddiqui & Wasif, 2025).

Moreover, predictive analytics enables continuous monitoring of risk throughout the project lifecycle. As new data is collected, AI models can update their predictions, allowing managers to respond dynamically to emerging risks. This real-time capability enhances the responsiveness and resilience of project teams, helping them navigate uncertainty more effectively than traditional static risk assessments.

Despite these advantages, there are challenges in implementing AI for risk assessment. The quality of predictions depends heavily on the availability and accuracy of data. Inconsistent or incomplete datasets can reduce the reliability of AI outputs, potentially leading to poor decisions if managers over-rely on the technology (Fridgeirsson et al., 2023). Additionally, organisational culture and governance structures influence how AI is adopted and trusted. Managers may resist AI tools if they perceive them as replacing human judgment, or if they are unsure how to interpret the outputs. Successful implementation therefore requires attention to both technical and social factors, ensuring that AI supports rather than undermines managerial decision-making.

In summary, predictive analytics offers powerful tools for enhancing risk assessment by identifying potential issues earlier and providing evidence-based insights. The distinction between automation and augmentation highlights the importance of human involvement in interpreting AI outputs. By combining AI capabilities with managerial expertise, project teams can achieve more effective, timely, and informed risk management, particularly in complex and international projects.

2.4.3 Future Directions: Technology Adoption and Trust in AI

The successful implementation of AI in project risk management is closely linked to how organisations adopt the technology and the level of trust managers place in AI systems. Even the most advanced AI tools are ineffective if they are not properly integrated into organisational practices or if managers are hesitant to rely on their outputs. Technology adoption is influenced by multiple factors, including organisational culture, managerial attitudes, perceived usefulness, and the availability of appropriate training and support (Venkatesh et al., 2012).

Organisations with a culture that encourages innovation and experimentation are more likely to successfully adopt AI. When managers perceive AI as a supportive tool rather than a replacement for human expertise, they are more inclined to use it effectively in decision making (Fridgeirsson et al., 2023). Conversely, in organisations where hierarchical decision-making or risk aversion dominates, AI adoption may be slower, and its outputs may be underutilised. This aligns with insights from the technology acceptance model, which suggests that perceived usefulness and ease of use strongly shape whether employees embrace new technologies (Davis, 1989).

Trust in AI systems is another critical factor shaping adoption. Managers must believe that AI recommendations are reliable, accurate, and relevant to the context of their projects (Sharma et al., 2024). Without trust, managers may ignore AI insights or rely on them inconsistently, reducing their effectiveness. Building trust often requires transparency in how AI systems generate predictions, the ability to validate outputs with historical or domain knowledge, and ongoing training to interpret AI insights correctly. Studies in organisational AI adoption highlight that perceived explainability and accountability are key drivers of trust, particularly in high-stakes environments such as international project management (Adamantiadou & Tsironis, 2025).

The interplay between technology adoption and trust is particularly important in multinational and cross-organisational projects. Different units or teams may have varying levels of familiarity with AI, different cultural attitudes toward technology, and different approaches to risk management. For example, European teams may prioritise structured risk assessment processes, while teams in other regions may rely more on experiential judgment. AI systems must therefore be flexible enough to support diverse practices while still providing consistent, reliable insights (Hashimzai & Mohammadi, 2023).

Looking ahead, the future of AI in project risk management is likely to involve more sophisticated integration with managerial decision-making processes. Generative AI, scenario simulation, and advanced predictive models can provide managers with richer insights, enabling proactive risk mitigation and dynamic adaptation to changing project conditions (Siddiqui & Wasif, 2025). However, these capabilities will only be realised if organisations cultivate a culture of trust, invest in training, and carefully align AI tools with existing governance structures.

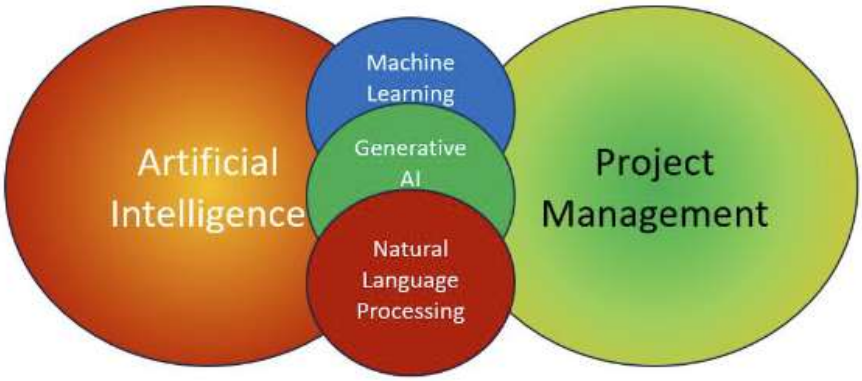

Figure 2 (Siddiqui & Wasif, 2025 Integration of AI models and Project Management)

In conclusion, technology adoption and trust are foundational to the future effectiveness of AI in project risk management. Organisations must focus not only on the technical capabilities of AI but also on human, cultural, and organisational factors. By fostering trust and embedding AI within decision-making processes, project managers can leverage AI to enhance risk identification, assessment, and mitigation, ultimately supporting better outcomes in complex and international project environments.

2.5 Rising usecases for AI in project Risk management

2.5.1 AI for Data-Driven Risk Identification

Artificial intelligence offers significant potential for enhancing risk management through predictive risk modelling and data-driven risk identification. Predictive risk modelling refers to using AI algorithms, particularly machine learning, to forecast potential risks based on historical and real-time project data. These models can detect patterns and correlations that might not be evident to human managers, enabling earlier identification of risks and more

proactive decision-making (Siddiqui & Wasif, 2025). By leveraging large datasets, AI can help predict a range of project risks, including schedule delays, cost overruns, and quality issues.

Data-driven risk identification builds on this capability by using AI to systematically process information from multiple sources, such as project reports, financial records, resource allocation data, and even external market or regulatory information. Unlike traditional risk identification methods that rely heavily on expert judgment or static checklists, AI can continuously monitor dynamic project environments and highlight emerging risks in real time (Fridgeirsson et al., 2023). This allows project managers to detect risks that may otherwise go unnoticed, particularly in complex or international projects with multiple interdependent factors.

Machine learning algorithms, including supervised and unsupervised learning, play a central role in predictive risk modelling. Supervised learning uses labeled historical data to predict the likelihood of specific outcomes, such as cost overruns or schedule slippage. Unsupervised learning, on the other hand, can identify hidden patterns or clusters of risk indicators without prior labeling, revealing potential risk factors that have not been explicitly considered before (Hashimzai & Mohammadi, 2023). For instance, unsupervised models may identify correlations between team composition, resource constraints, and project delays that were previously unrecognized.

The benefits of predictive risk modelling and data-driven identification are not only technical but also managerial. By providing evidence-based insights, AI supports more informed decision-making, enabling project teams to prioritise mitigation strategies according to the likelihood and impact of risks. Additionally, AI can enhance collaboration across organisational units or international teams by providing a shared, data-driven understanding of potential risks, reducing reliance on subjective judgment alone (Sharma et al., 2024).

However, implementing AI for predictive risk modelling requires attention to data quality and accessibility. Incomplete, inconsistent, or biased datasets can reduce the reliability of AI predictions and lead to incorrect conclusions. Therefore, organisations must establish robust data governance practices and ensure that project data is accurate, comprehensive, and regularly updated. Managers also need training to interpret AI outputs correctly and integrate them with contextual knowledge, ensuring that AI complements rather than replaces human judgment (Adamantiadou & Tsironis, 2025).

In conclusion, AI-driven predictive risk modelling and data-driven risk identification offer powerful tools for modern project management. By combining advanced analytics with managerial expertise, project teams can detect risks earlier, prioritise mitigation efforts more effectively, and navigate complex project environments with greater confidence. These approaches are particularly valuable in international and cross-organisational projects, where multiple variables interact and traditional risk management methods may be insufficient.

2.5.2 AI in Portfolio Risk Management, Limitations, and Human-AI Interaction

Beyond individual projects, AI is increasingly being applied to portfolio risk management, where organisations oversee multiple projects simultaneously. Managing a portfolio involves balancing resources, aligning projects with strategic objectives, and mitigating risks that may affect more than one project. AI tools can help by aggregating data from all projects, identifying patterns across the portfolio, and predicting potential risk concentrations or conflicts. This allows managers to prioritise attention and resources toward projects that pose the highest strategic or operational risks (Siddiqui & Wasif, 2025).

AI can provide automated dashboards that track key performance indicators, forecast portfolio-level risks, and simulate the impact of different resource allocation strategies. By doing so, AI supports strategic decision-making and enables a proactive approach to managing uncertainties across complex project environments (Fridgeirsson et al., 2023). For instance, AI might detect that two projects relying on the same critical resource are likely to face scheduling conflicts, prompting managers to adjust plans before these risks materialize.

However, AI in portfolio risk management has limitations, particularly in complex environments. Many projects involve uncertainties that are difficult to quantify, such as political, cultural, or regulatory factors. AI models rely heavily on historical and structured data, which may not capture these dynamic and context-specific risks. Overreliance on AI predictions without human judgment can therefore lead to incomplete or misleading assessments (Adamantiadou & Tsironis, 2025). Moreover, in highly innovative or unprecedented projects, historical data may be insufficient to train predictive models effectively, reducing their accuracy and applicability.

The interaction between human managers and AI systems is critical in addressing these limitations. AI should be viewed as a tool for augmentation rather than replacement. Human expertise is essential for interpreting AI outputs, contextualizing predictions, and making final decisions. For example, while AI may highlight potential resource conflicts across projects, managers must consider qualitative factors such as team dynamics, stakeholder priorities, and organisational strategy before taking action (Hashimzai & Mohammadi, 2023). Effective human-AI collaboration requires training managers to understand AI capabilities, limitations, and biases, as well as designing systems that provide transparent, explainable outputs that can be easily interpreted and trusted.

In conclusion, AI offers substantial benefits for portfolio risk management by providing data-driven insights across multiple projects and supporting proactive decision-making. However, its limitations in complex, uncertain, or novel environments mean that human judgment remains indispensable. The most effective risk management arises from a collaborative approach, where AI augments human decision-making while managers critically interpret and act upon the insights provided by these systems.

2.6 Conceptualisation

The literature reviewed in this chapter highlights two important developments in the field of project risk management. First, there is a clear and growing interest in the use of artificial intelligence to support project management processes. Existing studies show that AI-based tools, such as predictive analytics and machine learning, have the potential to improve the identification, assessment, and monitoring of risks. These technologies are often presented as a way to enhance efficiency, increase accuracy, and support more informed decision-making. As a result, the use of AI in project environments can be understood as an emerging and increasingly relevant trend.

At the same time, the literature also demonstrates that risk management cannot be understood solely as a technical or data-driven activity. A substantial body of research shows that risk is shaped by managerial perception, organisational context, and situational factors. Project managers interpret risks, prioritise them, and decide how to respond based on experience, judgement, and the specific conditions in which they operate. This suggests that even when advanced analytical tools are available, human interpretation remains central to how risk is managed in practice.

When these two streams of research are considered together, an important gap becomes visible. While the technical capabilities of AI in project management are increasingly well documented, there is limited understanding of how these tools are perceived and used by project managers in real organisational settings. In particular, existing research pays relatively little attention to how managers interpret AI-generated insights, how much they trust these systems, and how they integrate them into their decision-making processes. This gap is especially relevant in international project environments, where complexity, uncertainty, and contextual variation are high.

The conceptual focus of this thesis is therefore located at the intersection of AI use, managerial perception, and risk management practice. Rather than treating AI as a purely technical solution, the study approaches it as part of a broader decision-making context in which human judgement, organisational structures, and international conditions all play a role. This perspective shifts the focus from what AI can do in theory to how it is actually understood and applied in practice.

This conceptualisation provides the foundation for the research design. Since the aim is to explore how project managers perceive and utilise AI-based tools, a qualitative approach is appropriate for capturing subjective experiences, interpretations, and contextual influences. The following chapter therefore outlines the methodological choices made to investigate this relationship and to generate insights into the role of AI in project risk management within international organisations.

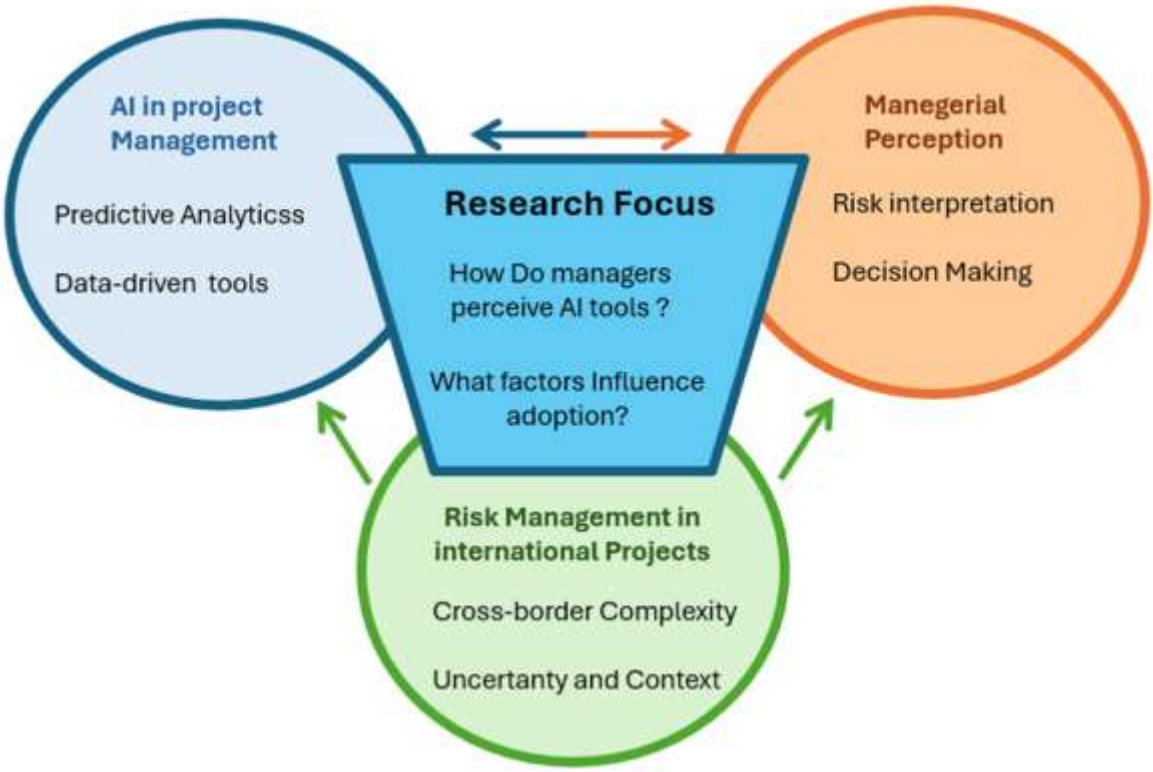

Figure 3 Conceptual Framework of AI, Managerial Perception, and Risk Management in International Projects

The figure illustrates the relationship between artificial intelligence (AI), managerial perception, and risk management within international project environments. The left component represents AI-based tools, including predictive analytics and data-driven decision support systems, which provide insights for risk identification and assessment. The right component reflects managerial perception and judgement, highlighting the role of interpretation, experience, and decision-making processes. The bottom component represents the context of international project risk management, characterised by cross-border complexity, uncertainty, and institutional variation. The central area indicates the primary research focus of this study, emphasising the limited u nderstanding of how project managers perceive and utilise AI tools in practice. The framework highlights that risk management outcomes are shaped not only by technological capabilities but also by human interpretation and contextual factors.

3 Methodology

3.1 Research Philosophy and Approach

All research is guided by underlying assumptions about reality, knowledge, and how understanding can be generated. These assumptions are often implicit, yet they fundamentally shape how a research problem is formulated, how data is collected, and how findings are interpreted. In social science research, and particularly within international business and project management, it is therefore necessary to make these philosophical foundations explicit. Clarifying the philosophy of science ensures internal coherence between the research problem, the chosen methodology, and the type of contribution the study aims to make.

This thesis investigates how project managers in international companies perceive and utilise AI based tools to support risk management in international projects. The focus on perception, interpretation, and utilisation indicates that the study does not treat risk or artificial intelligence as purely objective or technical phenomena. Instead, it recognises that both risk and technology acquire meaning through managerial interpretation and organisational context. As a result, the research requires a philosophical position that allows for multiple perspectives and acknowledges the socially constructed nature of organisational reality.

The purpose of this chapter is therefore to outline and justify the philosophical stance adopted in this thesis. The chapter will begin by discussing the ontological position of the study, which concerns assumptions about the nature of reality. It then addresses the epistemological position, which relates to how knowledge about that reality can be obtained. Following this, the research approach is presented, explaining how theory and empirical insights are connected through abductive reasoning. Finally, the implications of these philosophical choices for the methodological design of the study are discussed.

By making these assumptions explicit, the study ensures transparency and coherence in its overall design. The philosophical positioning presented here provides the foundation for the qualitative and cross organisational research strategy that follows in the methodology chapter.

3.1.1 Ontology: Constructionism

Ontology concerns the nature of reality and what can be said to exist within the world under investigation. In management and social science research, ontological positioning determines whether social phenomena are understood as objective and independent of human actors, or as constructed and shaped through interaction, interpretation, and context. Making this distinction is particularly important in studies that examine managerial behaviour and organisational practices.

Two broad ontological perspectives are commonly distinguished. An objectivist position assumes that social phenomena exist independently of the individuals who experience them. From this perspective, structures, risks, and technologies have an inherent and stable meaning that can be observed and measured. In contrast, a constructionist position argues that social

reality is continuously produced and reproduced through human interaction. Concepts such as risk, uncertainty, and even technology do not possess fixed meanings; instead, they acquire meaning through interpretation within specific organisational and cultural contexts.

This thesis adopts a constructionist ontological stance. Risk in international projects cannot be treated as a purely objective entity that exists independently of managerial judgement. Although certain events may generate measurable consequences, the identification, prioritisation, and interpretation of risk are shaped by how managers understand their environment. International projects often involve diverse stakeholders, cultural differences, and varying regulatory frameworks, all of which influence how potential threats and uncertainties are perceived. What is considered a major risk in one organisational or national context may be interpreted differently in another.

Similarly, artificial intelligence based tools cannot be understood as neutral or universally interpreted instruments. While AI systems are designed to analyse data and generate insights, their outputs must be interpreted by managers who decide whether to trust them, how to integrate them into decision processes, and how much weight to assign to their recommendations. The meaning and practical significance of AI tools therefore emerge through interaction between technology, managers, and organisational settings.

The constructionist position is particularly relevant in the field of international business. Organisations operating across borders are embedded in different institutional environments, cultural norms, and regulatory systems. These environments influence how managers interpret uncertainty and evaluate potential risks. Risk does not appear in a uniform manner across contexts; it is framed and understood through locally embedded practices and shared organisational assumptions. As a result, reality in international project settings cannot be reduced to objective indicators alone. It is shaped through social processes, communication, and managerial sensemaking.

Adopting a constructionist ontology also implies that knowledge about AI supported risk management must account for variation across organisations. A cross organisational study is therefore consistent with this ontological stance. If risk and technology use are socially constructed, then differences between firms are not merely deviations from a single objective model but meaningful expressions of distinct organisational realities. Examining multiple organisations allows the study to explore how different interpretations emerge and how they shape managerial practices.

This ontological position does not deny that material conditions, technologies, or external events exist. Rather, it emphasises that their significance for decision making depends on how they are interpreted. For example, an AI system may generate a risk prediction based on historical data, but whether that prediction influences managerial action depends on how it is understood and evaluated within the organisation. The constructed nature of reality therefore lies not in denying the existence of events, but in recognising that their meaning is not fixed.

By adopting constructionism, this thesis acknowledges that risk management and AI utilisation are embedded in organisational and international contexts. This position provides the foundation for exploring how project managers make sense of risk and technological tools, and it supports the qualitative and interpretive research design that follows. The next section will address the epistemological implications of this stance by explaining how knowledge about these constructed realities can be generated.

3.1.2 Epistemology: Interpretivism

While ontology concerns assumptions about the nature of reality, epistemology addresses how knowledge about that reality can be generated. In other words, epistemology defines what counts as valid knowledge and how a researcher can come to understand social phenomena. The epistemological position adopted in a study must be consistent with its ontological assumptions, as the understanding of reality influences the way knowledge about it is pursued.

In management research, two broad epistemological traditions are often contrasted. A positivist perspective assumes that social phenomena can be studied in a similar manner to natural sciences. From this viewpoint, knowledge is generated through objective measurement, hypothesis testing, and the identification of generalisable causal relationships. Researchers seek to minimise subjectivity and produce findings that can be replicated across contexts.

In contrast, an interpretivist perspective argues that social reality cannot be fully understood through detached observation alone. Because social phenomena are shaped by human interpretation and interaction, knowledge must be generated by examining how individuals make sense of their experiences. Interpretivism therefore emphasises meaning, context, and the subjective perspectives of social actors. Rather than aiming to uncover universal laws, interpretivist research seeks to understand how individuals interpret their environment and construct their reality.

This thesis adopts an interpretivist epistemology. The research problem focuses on how project managers perceive risk and utilise AI based tools within international projects. These phenomena cannot be adequately captured through quantitative measurement alone, as they involve individual judgement, organisational culture, and contextual interpretation. Understanding how managers experience and interpret risk requires engaging with their perspectives and exploring the meanings they attach to their practices.

An interpretivist approach is particularly appropriate for a study that examines managerial perception and technology use in international contexts. Project managers do not simply respond to objective indicators of risk or mechanically apply AI generated recommendations. Instead, they interpret information through prior experience, organisational expectations, and the specific circumstances of each project. Their decisions are shaped by how they understand both uncertainty and technological support systems. To capture this complexity, the research must prioritise access to managerial viewpoints and the meanings they assign to their actions.

This epistemological position has direct implications for the choice of method. Knowledge in this study is generated through qualitative inquiry, specifically through in depth engagement with project managers across organisations. Semi structured interviews allow participants to articulate how they perceive risk, how they evaluate AI tools, and how these tools influence their decision making. Such an approach recognises that insight emerges through dialogue and reflection rather than through detached measurement.

Interpretivism also aligns with the cross organisational design of the study. By exploring multiple organisations, the research acknowledges that meanings are context dependent and may vary across institutional and cultural settings. The goal is not to identify statistically generalisable patterns but to develop a nuanced understanding of how interpretations differ and why. This understanding can then contribute to theory development by revealing how risk perception and AI utilisation are shaped by organisational and international conditions.

Finally, the interpretivist stance supports the abductive reasoning adopted in this thesis. Because knowledge is viewed as emerging from the interaction between theory and empirical insight, the research process involves moving between existing literature and the interpretations expressed by participants. Rather than imposing fixed theoretical categories, the study remains open to refining or extending concepts based on the meanings uncovered during the investigation. In this way, epistemology, ontology, and research approach form a coherent foundation for the overall research design.

3.1.3 Research Approach: Abductive Reasoning

The research approach describes how theory and empirical investigation are related within a study. It clarifies whether research begins with established theory that is tested through data, whether it develops theory purely from observations, or whether it moves iteratively between theoretical ideas and empirical insights. The choice of approach must align with both the research problem and the philosophical foundations of the study.

In social science research, three main approaches are commonly distinguished: deductive, inductive, and abductive reasoning. A deductive approach begins with existing theory and formulates hypotheses that are tested through empirical data. The aim is often to confirm or reject predefined propositions and to produce generalisable findings. This approach is typically associated with positivist traditions and quantitative research designs.

An inductive approach, in contrast, begins with empirical observations and seeks to generate theory from the data. Rather than testing existing frameworks, the researcher allows patterns and concepts to emerge through analysis. Inductive reasoning is often associated with exploratory qualitative studies, particularly when little prior research exists on a topic.

While both approaches offer valuable strategies, neither fully captures the nature of this study. The relationship between AI, risk perception, and international project management has been discussed in existing literature, but the intersection of these elements remains underdeveloped.

There is therefore a need to engage with established theoretical perspectives while remaining open to new insights that may challenge or extend them.

For this reason, the thesis adopts an abductive research approach. Abductive reasoning can be understood as a process of moving back and forth between theory and empirical material in order to refine and develop conceptual understanding. Rather than beginning with fixed hypotheses or relying solely on emergent patterns, abductive research allows theoretical ideas to inform data collection and analysis while also permitting empirical findings to reshape theoretical assumptions.

This approach is particularly suitable for a study that seeks to explore how project managers perceive and utilise AI based tools in international risk management contexts. Existing literature provides important foundations regarding risk management frameworks, risk perception, and AI adoption in organisations. However, it does not offer a fully developed explanation of how these elements interact in practice across international firms. An abductive strategy allows the research to engage with these theoretical perspectives while remaining sensitive to unexpected insights that may emerge during interviews.

In practical terms, this means that the study will begin with a theoretical understanding derived from the literature review, including concepts such as managerial risk perception, technology adoption, and organisational context. These concepts will guide the development of the interview framework and initial analytical categories. During the empirical phase, however, attention will be given to themes and interpretations that do not fully align with existing theory. When such instances arise, the researcher will revisit the theoretical framework and consider whether refinement or extension is necessary.

The abductive approach therefore supports the overall ambition of the thesis to contribute to theory building rather than simple theory testing. By integrating empirical insights from multiple organisations with established conceptual foundations, the study aims to develop a more comprehensive understanding of AI supported risk management in international project environments. This approach ensures coherence with the constructionist ontology and interpretivist epistemology outlined above, as knowledge is viewed as emerging through iterative engagement with both theory and lived managerial experience.

3.2 Research Design

This study follows a qualitative and exploratory research design in order to examine how project managers perceive and utilise AI-supported tools within risk management processes in international projects. A qualitative approach was considered appropriate because the research focuses on understanding managerial interpretations, experiences, and decision-making practices within complex organisational and international environments rather than measuring predefined variables or testing causal relationships quantitatively. The study therefore seeks to capture how project managers make sense of risk, uncertainty, and AI-supported decision-making within real project contexts shaped by organisational structures, stakeholder relationships, and international complexity.

The research was designed as a cross-organisational study involving respondents from different professional and organisational environments rather than focusing on a single company or case. This design allowed the study to compare perspectives across industries, organisational structures, and levels of technological maturity while also identifying recurring patterns across different contexts. The inclusion of respondents from consultancy, telecommunications, energy, corporate reporting, and international development environments strengthened the ability of the study to explore both similarities and contextual differences in managerial approaches toward risk management and AI-supported systems. This cross-organisational perspective was particularly important given the international focus of the thesis, as risk perception and AI adoption were expected to vary depending on organisational culture, international exposure, governance structures, and operational environments.

The study also has a strongly exploratory character due to the evolving nature of AI integration within project management practices. While existing literature has increasingly examined AI-supported project management and digital decision-support systems, the practical integration of AI into managerial risk-related decision-making processes remains uneven and still developing across organisations and industries. Rather than testing predetermined hypotheses, the research therefore aimed to explore emerging patterns, recurring perceptions, and practical experiences related to AI-supported risk management in international projects. This exploratory orientation aligns closely with the abductive research approach adopted in the study.

Instead of treating theory and empirical data as fully separate stages of the research process, the abductive approach allowed continuous movement between empirical observations and theoretical interpretation throughout the study. Initial theoretical concepts derived from the literature review and conceptual framework guided the early stages of the research design and interview development. However, as interviews progressed, emerging empirical insights continuously informed the analytical direction of the study and led the researcher back to the literature in order to refine interpretations and identify additional theoretical connections. Themes such as communication complexity, contextual interpretation, organisational influence, and conditional trust in AI became increasingly central as the empirical material developed, resulting in a more iterative relationship between theory and data throughout the research process.

Overall, the chosen research design supported the objective of generating rich, context-dependent insights into managerial perceptions and practices while also allowing for cross-organisational comparison and theoretically informed interpretation. The combination of a qualitative, exploratory, cross-organisational, and abductive design was therefore considered suitable for examining the evolving relationship between AI-supported tools, managerial judgement, and risk management within international project environments.

3.3 Data Collection method

This study uses semi-structured interviews as the primary method of data collection. This approach was considered appropriate because it allows participants to describe their experiences, interpretations, and professional practices in their own words, while still maintaining enough structure to ensure that the central research themes are consistently addressed across interviews. The interview guide focused on areas such as risk perception, risk management practices, organisational and international influences, the use of AI-supported tools, and managerial trust in AI-generated insights. At the same time, the semi-structured format provided the flexibility necessary to explore unexpected themes and emerging insights during the interview process. This flexibility was particularly important given the study's abductive research approach, which required continuous interaction between empirical observations and theoretical interpretation throughout the research process.

Participants were selected using purposive sampling, meaning that interviewees were chosen based on their relevance to the research topic and their experience with international projects, project risk management, and digital or AI-supported tools. Since the thesis focuses specifically on international project environments, particular attention was given to selecting respondents from different professional, organisational, and cultural backgrounds in order to capture variation in perspectives and experiences. The final sample therefore included respondents from consultancy, telecommunications, energy, data-driven corporate environments, and international development projects. In some cases, additional participants were identified through professional networks, allowing the study to incorporate a broader range of international and organisational perspectives.

The interview process itself followed an abductive logic rather than relying on a completely fixed interview structure. The initial interview guide was developed from the literature review and the a priori conceptual framework, which connected managerial perception, AI-supported project management, and risk management in international projects. However, as interviews progressed and empirical insights emerged, the researcher continuously revisited the literature and adjusted the focus of subsequent interviews accordingly. Early interviews revealed the importance of themes such as communication complexity, organisational influence, trust in AI, contextual interpretation, and the limitations of AI in stakeholder-sensitive environments more strongly than initially anticipated. As a result, later interviews included additional probing questions and more detailed discussions related to these emerging themes. In this sense, the interview guide functioned as an evolving analytical instrument shaped through the continuous interaction between theory and empirical findings.

The collected interview material was analysed using thematic analysis supported by a three-level coding process. The analysis began with repeated reading and familiarisation with the interview transcripts, followed by the identification of recurring concepts, experiences, and interpretations within the data. These initial codes were then grouped into broader analytical categories and later developed into higher-order themes through continuous comparison across interviews. Rather than emerging from isolated statements, the final themes were developed

through recurring patterns identified across multiple respondents operating in different organisational and international contexts. The analysis therefore focused not only on identifying similarities across interviews, but also on interpreting contextual variations influenced by factors such as industry background, organisational structure, international exposure, managerial experience, and level of AI integration. Throughout the analytical process, emerging findings were continuously compared with the theoretical framework and existing literature, allowing empirical insights to refine and expand the theoretical interpretation of the research problem. This iterative movement between theory and empirical observations reflects the abductive logic underpinning the study.

3.4 Development of the Semi-Structured Interview Guide

The primary semi-structured interview guide seen in **Appendix 1** was developed based on the a priori conceptual framework presented at the end of the literature review. The framework connected three central theoretical dimensions relevant to the research problem: **AI in project management**, **managerial perception and decision-making**, and **risk management in international projects**. These dimensions formed the theoretical foundation for the construction of the interview questions and ensured alignment between the literature review, research questions, and empirical data collection process.

The interview guide was structured into thematic sections corresponding to the main elements of the conceptual framework (**Figure 3**). Questions related to managerial perception and risk interpretation were developed based on literature surrounding risk perception, behavioural decision-making, and managerial judgement (Slovic, 1987; Kahneman & Tversky, 1979; March & Shapira, 1987). These questions explored how respondents understood uncertainty, interpreted risk, and approached decision-making within project environments. Questions concerning international and organisational influences were informed by literature on project complexity, organisational governance, institutional differences, and cross-border project management (Geraldi et al., 2011; Hofstede, 2001; North, 1990). This section aimed to explore how organisational structures, communication processes, and international complexity shape risk management practices in practice.

The AI-focused section of the interview guide was developed from literature concerning AI-supported project management, predictive analytics, technology adoption, and data-driven decision support (Russell & Norvig, 2021; Davis, 1989; Venkatesh et al., 2012). These questions examined how respondents used AI-supported tools, how they perceived their usefulness, and how AI-generated insights were incorporated into project risk management processes. Additional questions concerning trust, adoption, and human–AI interaction were included to explore how project managers balanced technological support with personal experience and contextual judgement.

The use of semi-structured interviews allowed for flexibility during the data collection process while still maintaining alignment with the theoretical framework and research objectives. The initial interview guide represented the first version of the data collection framework and was primarily informed by the literature review and the a priori conceptual framework. However,

due to the abductive research approach adopted in this study, the interview process evolved gradually throughout the research process. As additional empirical insights were gathered through early interviews, the researcher continuously revisited the literature review and theoretical framework in order to compare emerging findings with existing theory. This iterative movement between theory and empirical observations allowed new insights from the interviews to influence the focus of subsequent interviews and probing questions.

Early interviews highlighted the importance of themes such as trust in AI, communication complexity, organisational influence, contextual interpretation, and the limitations of AI in stakeholder-sensitive environments more strongly than initially anticipated. As a result, later interviews included additional probing questions and more detailed follow-up discussions related to these emerging themes. In this sense, the interview guide was not treated as a completely fixed instrument, but rather as a flexible framework that evolved through the continuous interaction between empirical observations and theoretical interpretation. This process reflects the abductive logic of the study, where theory informed the initial research direction while empirical findings simultaneously contributed to the refinement of theoretical understanding throughout the research process (Dubois & Gadde, 2002).

Table 1 illustrates how the conceptual framework informed the development of the interview guide and how individual question groups were connected to the theoretical dimensions identified in the literature review.

Table 1 development of initital interview guide

Conceptual Framework Dimension	**Literature Focus**	**Related Interview Questions**
Managerial Perception	Risk perception, decision-making, interpretation of uncertainty	Q2, Q3, Q4
Risk Management in International Projects	Cross-border complexity, organisational influence, contextual uncertainty	Q5, Q6
AI in Project Management	Predictive analytics, AI-supported tools, data-driven decision support	Q7, Q8
Trust and Technology Adoption	Trust in AI, adoption factors, perceived usefulness	Q9, Q10

Human–AI Interaction	Human judgement, AI support, future development of AI in risk management	Q11, Q12

3.5 Interview participant selection

The interview participants were selected through purposive sampling based on their experience with international projects, project risk management processes, and exposure to AI-supported tools within professional environments. The respondents represent a range of industries and organisational contexts, including consultancy, infrastructure, telecommunications, renewable energy, and industrial project environments.

All participants consented to taking part in the research and agreed to the use of their professional perspectives within the study. To improve clarity and analytical traceability throughout the analysis and discussion chapters, respondents are from this point onwards referred to using interview identifiers (Int1–Int10). These identifiers are used consistently when referring to interview statements, quotations, and analytical observations.

Table 2 - Overview of Interview Participants

Interview Code	**Name**	**Position / Role**	**Industry / Organisational Context**	**International Project Experience**	**AI Exposure / Usage**
Int1	Alice	Junior Project Manager	International project environment	Moderate–High	Moderate
Int2	Alina	Senior Project Manager	Energy / infrastructure / development projects	High	High
Int3	Francisco	Project Management Professional	International consultancy / development projects	High	Moderate
Int4	Gabriela	Project Coordinator	International project coordination	Moderate–High	Moderate

Int5	Igor	Senior Project Manager	Oil & gas / industrial projects	High	Limited–Moderate
Int6	Laura	Senior Project Manager	International project environment	Moderate–High	Moderate
Int7	Siniša	Senior Project Manager	International consultancy / EU-funded projects	High	Moderate–High
Int8	Tahir	Project Management Professional	International project management environment	High	High
Int9	Zhang	Financial and Project Reporting Specialist/Project Manager	Renewable energy / international corporate environment	High	High
Int10	Zoran	Senior Project Manager	Telecommunications / international projects	High	Moderate

3.6 Theme Development Across Interviews

The final themes emerged through repeated patterns identified across multiple interviews rather than through isolated statements from individual respondents. Although respondents described their experiences from different organisational, sectoral, and international contexts, several underlying interpretations remained highly consistent throughout the dataset. The analysis therefore focused on identifying recurring perspectives and shared understandings across interviews while also recognising contextual differences shaped by organisational structures, industries, and levels of international exposure.

3.6.1. Contextual Complexity Shapes Risk Management

One of the strongest recurring themes across the interviews was the idea that risk management in international projects is heavily shaped by contextual complexity. Respondents consistently connected risk not only to technical or financial factors, but also to cultural differences, political environments, stakeholder behaviour, communication structures, and organisational diversity.

Int8 described international projects as "more complex" due to "managing communication across cultures," "different time zones," and the fact that "organizational structures differ." Similarly, Int3 explained that "understanding cultural context [is] essential" and that "government regulations influence projects," while "climate affects timelines." Int10 also highlighted "greater risks outside EU," "frequent changes in conditions," and "travel risks in certain countries."

This pattern also appeared in less externally focused organisational contexts. Int1 connected project risks to "fragmented chain of command," "culture of shifting blame," and "slow response to problems." Int6 similarly explained that "companies differ in project and risk approaches" and that "risks vary significantly by country." Across interviews, respondents consistently described risk as context-dependent and shaped by environmental, organisational, and international complexity rather than purely formal project calculations.

3.6.2. Risk Management as a Continuous and Proactive Process

A second recurring theme concerned the perception of risk management as a continuous and proactive process rather than a one-time assessment activity. Respondents consistently emphasised early identification, ongoing monitoring, reassessment, and adaptation throughout the project lifecycle.

Int3 explained that "risk updated regularly" because "project conditions [are] constantly changing," while the "risk matrix [is] updated every six months" and continuously revised during implementation. Similarly, Int8 stressed the importance of identifying risks "early and continuously," "not just at kickoff," because "late solutions are complex/expensive."

This proactive orientation also appeared in more operational and technical environments. Int5 emphasised the need to "anticipate risks early" and "account for risks as early as possible." Int9 similarly described how risks are managed through "anticipating issues early," "address[ing] delays or inconsistencies upfront," and "build[ing] checks into systems." Even respondents operating in less structured environments recognised the consequences of delayed risk identification. Int1 reflected that a project risk "should have been identified at contract stage" but instead escalated into delays and operational complications.

Although approaches differed in formality and structure, the interviews consistently framed risk management as an ongoing process requiring constant reassessment and adaptation.

3.6.3. Formal Structures Are Complemented by Informal Practices

Another important theme emerging across the interviews was that formal risk management systems alone were considered insufficient. While many respondents described structured processes such as risk registers, workshops, reporting systems, and escalation procedures, they also consistently highlighted the importance of informal communication, intuition, and experiential judgement in identifying and managing risks.

Int2 described "regular internal meetings," "stand-up meetings," and "management-level meetings," but also explained that risks are often identified through "office discussions," "brainstorming sessions," and even "discussions during lunch/coffee." Similarly, Int8 explained that "important risks emerge informally," where "casual conversations reveal risks," and even intuition such as when something "doesn't feel right" can act as an early warning signal.

Int5 also noted that despite structured corporate systems, "learning happens informally" through "internal discussions or gossip," while there was "no structured lessons learned process." Int1 similarly described environments where risks were often recognised only after problems appeared due to weak formal structures and fragmented organisational processes.

Across the interviews, respondents consistently described effective risk management as dependent on both formal organisational systems and informal human interaction, communication, and experiential awareness.

3.6.4. Communication and Culture as Central Mechanisms of Risk Control

Communication emerged as one of the most consistently referenced mechanisms through which risks are identified, escalated, and controlled within international project environments. Respondents repeatedly connected successful risk management to transparency, openness, documentation, and culturally sensitive communication practices.

Int8 stated that "transparency and open communication" are essential because "hiding risks makes things worse," while organisations should create "culture[s] of openness" where "people feel comfortable speaking up." Similarly, Int1 highlighted the need to be "mindful of tone and cultural expectations," especially where "language barriers affect understanding" and "explicit communication [is] needed."

Communication also emerged as a practical control mechanism within technical and operational environments. Int9 explained that "regular communication and check-ins" help "reduce ambiguity," while "different ways of working" and "different definitions/standards" create risks of misalignment across international teams. Int10 similarly described how project managers must continuously "inform stakeholders about risks," including "management, sales, [and] customer[s]."

Although communication challenges varied across sectors and organisational structures, respondents consistently framed communication and cultural understanding as central mechanisms through which uncertainty and risk are managed in practice.

3.6.5. AI as an Augmenting but Limited Partner in Risk Management

The final major theme concerned the role of AI within project risk management. Across interviews, respondents consistently described AI as a useful support mechanism for efficiency, information processing, and analytical assistance, while simultaneously emphasising its limitations in contextual interpretation, judgement, and decision-making.

Int2 described using "AI for drafting communication," "basic research," and "extracting key information," while stressing that "AI not used for final decisions" and that "trust own judgement" remains central. Int3 similarly described AI as "second opinion" and "complementary tool," but stated that managers should "never rely 100% on AI."

This pattern remained highly consistent across respondents with both high and low AI exposure. Int8 explained that AI acts as "second pair of eyes" and "sounding board," but that "human judgment still essential" because AI "lacks contextual understanding." Int9 similarly argued that AI "should not replace human judgment" and that managers must "consider business context" and "investigate further manually."

Even respondents with limited AI adoption expressed similar perspectives. Int10 described AI as useful for "ideas or direction" and "large data analysis," while warning about "danger in relying completely on AI." Int6 also argued that projects are "complex and multifactorial" and therefore "AI cannot replace human decisions."

Although respondents differed in the extent of AI usage and technological exposure, the interviews consistently positioned AI as an augmenting rather than autonomous mechanism within project risk management. Human judgement, contextual understanding, and managerial responsibility remained central across all interviews.

3.7 Contextual Variations and Mediating Factors

Although the final themes remained highly consistent across the interviews, important variations emerged in how respondents interpreted and approached risk management and AI-supported decision-making. These variations were not treated as contradictions within the dataset, but rather as contextually shaped differences influenced by mediating factors such as organisational structure, sectoral background, level of international exposure, managerial experience, and degree of AI integration within daily work practices. These differences are visualised in **table 3**.

One important mediator was the organisational environment in which respondents operated. Respondents working within highly structured corporate or technical environments generally described more formalised and system-embedded approaches to risk management. For

example, Int9 referred to “strong controls in financial reporting,” “validation processes,” and “structured dataflows,” reflecting a highly process-oriented and data-driven approach to risk control. In contrast, respondents operating in less structured organisational environments described risk management as more reactive and dependent on individual initiative. Int1 referred to a “fragmented chain of command,” “lack of organisational support,” and situations where “risks [were] identified after issues occur.” These differences influenced how respondents perceived both organisational risk management maturity and the usefulness of AI-supported systems.

Sectoral background also influenced how risks were interpreted and prioritised. Respondents working in telecommunications and highly technical environments focused more strongly on operational continuity, technical dependencies, and execution-related risks. Int10 connected risk management to “project execution,” “testing and validation,” and “delivery constraints.” Meanwhile, respondents working in consultancy and international development environments placed stronger emphasis on stakeholder management, political uncertainty, communication complexity, and institutional differences. Int6 described risks associated with “political influence on experts,” “unpredictable client behaviour,” and “country-level assessments.” Similarly, Int4 highlighted geopolitical and macroeconomic risks connected to “energy prices” and regional crises.

Another important mediator concerned the level of AI exposure and technological integration within respondents’ professional environments. Respondents with greater exposure to AI-supported or data-driven systems generally expressed stronger confidence in the analytical value of AI tools, particularly regarding efficiency, pattern recognition, and information processing. Int8 described AI as useful for “handling large information volumes,” “extract[ing] key points quickly,” and acting as a “second pair of eyes.” Similarly, Int9 highlighted the ability of automated systems and dashboards to improve “visibility,” “identify anomalies,” and “reduce human error.” In contrast, respondents with lower AI exposure or stronger organisational restrictions placed greater emphasis on concerns surrounding reliability, transparency, and contextual limitations. Int10 stressed that AI outputs “may not be accurate” and “must be cross-checked,” while Int1 raised concerns regarding “lack of transparency” and AI’s inability to manage “complex situations.”

Differences were also visible in relation to managerial experience and accumulated international exposure. More experienced project managers generally demonstrated more adaptive and context-sensitive approaches toward risk interpretation and decision-making. Senior respondents frequently emphasised flexibility, stakeholder awareness, escalation mechanisms, and contextual judgement developed through practical experience across different environments. Less experienced respondents, while still recognising similar risks and organisational challenges, more frequently focused on operational uncertainty, lack of guidance, and dependence on existing organisational systems.

These contextual differences align with experiential learning perspectives within international business literature, particularly the Uppsala model’s emphasis on gradual knowledge accumulation through international exposure and practical experience (Johanson & Vahlne,

1977). From this perspective, variations in responses reflected differences in accumulated experiential knowledge rather than inconsistencies within the findings themselves. Despite these contextual variations, the core thematic patterns remained highly stable across interviews, reinforcing the broader analytical conclusions of the study.

Table 3 "theme distribution matrix"

Theme Distribution Matrix												
Core Themes	Interviews										Prevalence (High/Med/Low)	Key Observation
	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10		
Risk Management Approaches	~	✓	✓	✓	~	✓	✓	✓	✓	✓	HIGH	Structured Approaches dominate, with some reactive practices remaining
Organisational and Contextual Influence	~	✓	✓	~	✓	✓	✓	✓	✓	~	HIGH	Organisation type, maturity and governance strongly shape risk
Communication and Complexity	X	✓	X	~	✓	✓	✓	~	✓	✓	MEDIUM	Communication issues and stakeholder complexity are major sources of risk
AI Usage in Risk Management	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	HIGH	All iterviewees use AI in some capacity, mainly as a support tool
Trust and Limitations of AI	✓	✓	✓	✓	~	✓	✓	✓	✓	✓	HIGH	Trust is conditional: concerns about accuracy, data and over-reliance are common
Human Judgment in Decision-Making	✓	✓	✓	✓	✓	~	✓	✓	✓	✓	HIGH	Human judgment remains central - Ai assists but does not replace
Intensity	Strong presence		Moderate presence		Low presence		Not mentioned					

3.8 Quality Criteria and Methodological Limitations

In qualitative research, the quality of the study is assessed through criteria such as credibility, dependability, and transparency. This study aims to ensure credibility by collecting rich and detailed data through semi-structured interviews, allowing participants to explain their experiences and perspectives in depth. By focusing on participants with relevant and diverse professional backgrounds, the study also strengthens the relevance and trustworthiness of the findings.

Dependability is addressed by maintaining a clear and structured research process. The steps taken in data collection and analysis are documented to ensure that the approach is transparent and can be understood by others. At the same time, the researcher remains aware of their role in interpreting the data, recognising that qualitative analysis involves a degree of subjectivity. Efforts are made to stay consistent in coding and interpretation, while linking findings back to existing theory.

4. Analysis

This chapter presents the analysis of the empirical data collected through semi-structured interviews with project managers working across different organisational, industrial, and international contexts. The purpose of the analysis is to explore how project managers perceive and manage risk in practice, and how AI-supported tools are understood, utilised, and evaluated within these processes. Rather than examining each interview as an isolated case, the analysis focuses on identifying recurring patterns, shared interpretations, contextual differences, and broader thematic relationships across the dataset.

The analysis follows the abductive research approach outlined in the methodology chapter. Initial theoretical concepts derived from the literature review and the a priori conceptual framework informed the early stages of the coding and analytical process. However, the analysis did not follow a strictly linear movement from theory to data. Instead, empirical observations continuously influenced the interpretation of the material and prompted repeated returns to the literature throughout the research process. As additional interviews were conducted and coded, emerging themes such as communication complexity, contextual interpretation, stakeholder sensitivity, organisational influence, and conditional trust in AI became increasingly central to the analysis. This iterative movement between empirical findings and theoretical understanding allowed the analytical focus to evolve gradually throughout the study rather than remaining fixed from the outset.

The interview material was analysed through a three-level coding process, which has been described in detail within the methodology chapter. Initial statements and recurring concepts were first identified within individual interviews and then compared across respondents in order to identify broader analytical patterns. The final themes presented in this chapter therefore emerged through repeated similarities across multiple interviews rather than from isolated statements or individual experiences. At the same time, contextual differences between respondents were treated as analytically important rather than contradictory, particularly where variations could be linked to organisational structures, sectoral backgrounds, international exposure, managerial experience, or levels of AI integration.

The findings demonstrate that risk management within international project environments is perceived as a highly contextual and continuously evolving process shaped by organisational structures, communication dynamics, stakeholder relationships, and external environmental conditions. Across the interviews, respondents consistently described risk as extending beyond technical calculations or formal procedures, emphasising instead the importance of practical experience, contextual awareness, communication, and adaptive decision-making. Similarly, AI-supported tools were rarely perceived as autonomous decision-making systems. Instead, respondents largely described AI as an augmenting mechanism used for support functions such as information processing, forecasting, validation, drafting, or analytical assistance, while final decisions remained strongly dependent on human judgement and contextual interpretation.

The chapter is structured around the five overarching themes that emerged from the empirical material. The first sections examine how contextual complexity shapes risk management practices and how respondents perceive risk as a continuous and proactive process. The analysis then explores the relationship between formal organisational structures and informal practices, particularly regarding communication, escalation, and experiential learning. The later sections focus on communication and culture as central mechanisms of risk control, followed by the role of AI-supported systems within managerial risk-related decision-making processes. Throughout the chapter, empirical findings from different interviews are compared and interpreted collectively in order to demonstrate how the identified themes emerged consistently across different organisational and international environments.

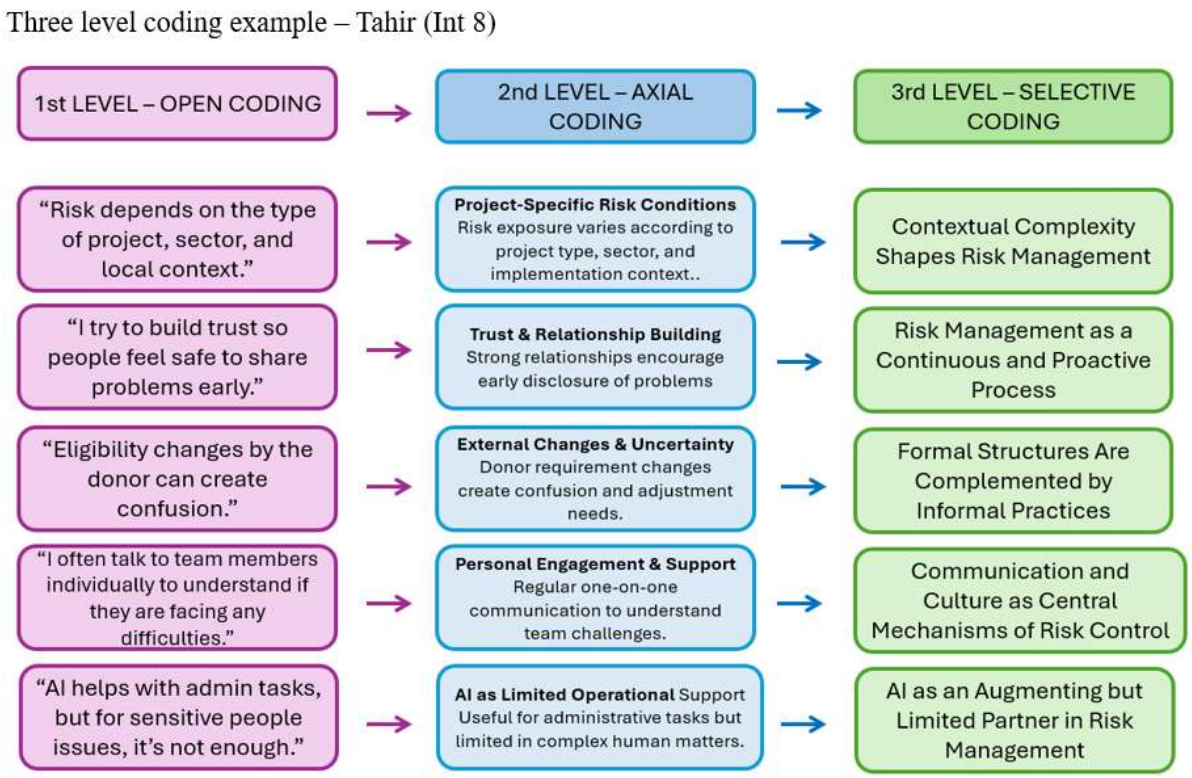

Figure 4 "Example of interview coding process visualised - Tahir (Int 8) Interview"

4.1 Understanding of Risk in Project Environments

The analysis demonstrates that risk is understood in different ways across project environments, although several common patterns emerged consistently throughout the interviews. Across most respondents, risk was primarily associated with anything that could negatively affect project execution, timelines, resources, or delivery outcomes. Int5 defined risk broadly as "anything jeopardizing time or resources," while also connecting risk to "procurement issues," "execution challenges," and "contractual relationships." Similarly, Int10 described risks in relation to "project execution," "testing and validation," and "delivery

constraints," reflecting a practical and operational understanding of risk linked closely to project implementation. Int3 also connected risk to "resource allocation risks," "unexpected circumstances," and the need to "anticipate possible events" during project planning and implementation. These perspectives reflect a shared understanding of risk as something capable of disrupting project performance, delivery, and organisational objectives.

At the same time, the interviews revealed a much broader understanding of risk extending beyond technical or operational concerns. Respondents frequently referred to organisational, political, institutional, cultural, and stakeholder-related risks that shape project implementation in international environments. Int7 described working in "large-scale project[s] in Nigeria" involving "risk of corruption," "risk of fraud or misuse of funds," and "stakeholder influence risk." Similarly, Int3 explained that "government regulations influence projects," while "political instability risk" and "geopolitical shift impact" may require organisations to "redesign project activities" and adjust stakeholder relationships. Int2 also highlighted risks connected to "staff changes on client side," "shift in EU priorities," and "political/institutional changes," which could result in situations where "deliverables become invalid" or where projects need to be "restructure[d]." These findings suggest that respondents did not perceive risk as limited to predefined categories, but rather as strongly shaped by the broader institutional and international environment within which projects operate.

Another highly consistent finding concerned the dynamic nature of risk. Across interviews, respondents repeatedly described risk as something that evolves continuously throughout the project lifecycle rather than remaining static. Int7 explicitly stated that "risk is not static" and that "risk evolves with project[s]," emphasising the need to "revisit risk matrix regularly," "reassess assumptions," and "identify new risks." Similarly, Int3 described how "risk updated regularly" because "project conditions [are] constantly changing," while "risk matrix [is] updated every six months" and revised throughout implementation. Int8 also emphasised the importance of identifying risks "early and continuously," arguing that "late solutions are complex/expensive." This continuous and iterative understanding of risk management appeared across nearly all interviews regardless of industry or organisational structure.

The analysis also indicates that risk perception is closely connected to the professional background and organisational environment of the respondent. In more technical or structured environments, respondents tended to frame risks in relation to operational reliability, technical execution, and process control. Int5, drawing from oil and gas experience, discussed risks such as "drilling through low-pressure zones," "budget overruns," and "poor well performance," emphasising the importance of "proper risk identification" within highly technical project environments. Similarly, Int9, working in data-driven reporting environments, connected risks to "different definitions/standards," "data inconsistencies," and process visibility issues affecting decision-making quality. In contrast, respondents operating in stakeholder-intensive environments placed greater emphasis on communication and relational risks. Int7 described how an "email describing low standards" was "accidentally copied [to a] beneficiary," resulting in stakeholders feeling "disrespected" and creating a "risk of team replacement." Int1 similarly

highlighted risks associated with “fragmented chain of command,” communication misunderstandings, and organisational blame culture.

Differences were also visible in how formally risk itself was conceptualised and managed. Several respondents described highly structured and formalised approaches involving risk matrices, reporting systems, escalation mechanisms, and periodic reviews. Int3 referred to “risk matrix developed at proposal stage,” “formal risk matrix usage,” and “consistent methodology across projects.” Int5 similarly described “structured approach in large company,” “mandatory risk documentation,” and the requirement to identify “risks, likelihood, [and] impact” as part of formal project approval systems. At the same time, more informal understandings of risk also emerged across the interviews. Int2 explained that risks are often identified through “office discussions,” “informal brainstorming sessions,” and even “discussions during lunch/coffee.” Int8 similarly described situations where risks emerge through intuition and informal awareness when something “doesn’t feel right.” These findings suggest that while formal systems remain important, respondents also rely heavily on practical judgement, communication, and informal interaction when interpreting and identifying risks in practice.

Overall, the findings indicate that risk within international project environments is perceived as a highly contextual, dynamic, and multi-dimensional phenomenon. Although respondents consistently associated risk with threats to project performance and delivery, the interviews demonstrate that risk perception extends far beyond technical calculations or formal procedures. Instead, organisational structures, communication dynamics, political conditions, stakeholder relationships, cultural environments, and practical managerial experience all shape how risks are interpreted and prioritised in practice. These contextual differences provide an important foundation for understanding how project managers subsequently approach risk management processes and position AI-supported tools within decision-making practices.

4.2 Risk Management Approaches and Practices

The analysis demonstrates that risk is understood in different ways across project environments, although several common patterns emerged consistently throughout the interviews. Across most respondents, risk was primarily associated with anything that could negatively affect project execution, timelines, resources, or delivery outcomes. Int5 defined risk broadly as “anything jeopardizing time or resources,” while also connecting risk to “procurement issues,” “execution challenges,” and “contractual relationships.” Similarly, Int10 described risks in relation to “project execution,” “testing and validation,” and “delivery constraints,” reflecting a practical and operational understanding of risk linked closely to project implementation. Int1 also described risk as something that “threatens successful delivery,” particularly when experts do not fulfil responsibilities, delays occur internally, or project outcomes and payments are affected. These perspectives reflect a shared understanding of risk as something capable of disrupting project performance, delivery, and organisational objectives.

At the same time, the interviews revealed a much broader understanding of risk extending beyond technical or operational concerns. Respondents frequently referred to organisational, political, institutional, cultural, and stakeholder-related risks that shape project implementation in international environments. Int7 described working in a "large-scale project in Nigeria" involving "risk of corruption," "risk of fraud or misuse of funds," and "stakeholder influence risk." Similarly, Int3 explained that "government regulations influence projects," while "political instability risk" and "geopolitical shift impact" may require organisations to "redesign project activities" and adjust stakeholder relationships. Int4 also identified risks across "political, financial, technological, and operational domains," while emphasising the importance of "regional variation and local context." These findings show that respondents did not perceive risk as limited to predefined technical categories, but as strongly shaped by the broader institutional and international environment within which projects operate.

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The analysis also indicates that risk perception is closely connected to the professional background and organisational environment of the respondent. In more technical or structured environments, respondents tended to frame risks in relation to operational reliability, technical execution, and process control. Int5, drawing from oil and gas experience, discussed risks such as "drilling through low-pressure zones," "budget overruns," and "poor well performance," emphasising the importance of "proper risk identification" within highly technical project environments. Similarly, Int9, working in data-driven reporting environments, connected risks to "data quality," "timelines," and "decision-making," noting that "small data issues can have big impact." In contrast, respondents operating in stakeholder-intensive environments placed greater emphasis on communication and relational risks. Int7 described how an "email describing low standards" was "accidentally copied [to a] beneficiary," resulting in stakeholders feeling "disrespected" and creating a "risk of team replacement."

Contextual complexity was also visible in how respondents connected risk to organisational conditions. Int1 strongly linked risk to internal organisational dysfunction, including a "fragmented chain of command," "outdated budgeting systems," and a "culture of shifting blame." This shows that risk was not only perceived as something external to the project, but also as something generated by weak internal structures and unclear responsibilities. Int6 made a similar point from a broader organisational perspective, explaining that "companies differ in

project and risk approaches" and that the application of risk management depends on "tools and culture." This supports the pattern that organisational context influences not only how risks are managed, but also how they are recognised and prioritised in the first place.

Differences were also visible in how formally risk itself was conceptualised and managed. Several respondents described highly structured and formalised approaches involving risk matrices, reporting systems, escalation mechanisms, and periodic reviews. Int3 referred to a "risk matrix developed at proposal stage," "formal risk matrix usage," and "consistent methodology across projects." Int5 similarly described a "structured approach in large company," "mandatory risk documentation," and the requirement to identify "risks, likelihood, [and] impact" as part of formal project approval systems. Int4 also described "structured risk identification in bidding phase," including the assessment of "likelihood, impact, and mitigation strategies." At the same time, more informal understandings of risk also emerged. Int2 explained that risks are often identified through "office discussions," "informal brainstorming sessions," and even "discussions during lunch/coffee."

Overall, the findings indicate that risk within international project environments is perceived as a highly contextual, dynamic, and multi-dimensional phenomenon. Although respondents consistently associated risk with threats to project performance and delivery, the interviews demonstrate that risk perception extends far beyond technical calculations or formal procedures. Instead, organisational structures, communication dynamics, political conditions, stakeholder relationships, cultural environments, and practical managerial experience all shape how risks are interpreted and prioritised in practice. This contextual understanding provides the foundation for the following section, which examines how risk management becomes a continuous and proactive process across different organisational settings.

4.3 Organisational Influence on Risk Management

The analysis shows that organisational context plays a central role in shaping how risk is perceived and managed in project environments. Across the interviews, clear differences emerged between organisations with structured and formalised risk management systems and those where risk handling was more decentralised and dependent on individual judgement. These differences influenced not only the tools and procedures used, but also how consistently risks were identified, communicated, escalated, and addressed.

In more structured organisational environments, risk management was supported by formal processes, templates, documentation requirements, and governance mechanisms. Int3 described the use of a "risk matrix developed at proposal stage," which was then "updated in inception report" and reviewed through "continuous updates during implementation." This indicates a lifecycle-based approach where risk management is embedded into the project structure from the beginning rather than treated as an isolated activity. Int3 also noted a "risk matrix approach used across organisation" and a "consistent methodology across projects," showing that risk management practices were standardised at organisational level.

A similar pattern appeared in Int5's interview, where risk management was strongly connected to formal corporate systems. Int5 described a "structured approach in large company," where "risk documentation [is] required" and projects must "justify inclusion in CAPEX plan." He also explained that risks are assessed through criteria such as "likelihood" and "impact," with the level of detail increasing as the project matures. This reflects a highly formalised and stage-based approach to risk management, especially in technical and capital-intensive project environments.

Structured risk management was also visible in data-driven organisational settings. Int9 described risk control through "data validation processes," "regular reporting cycles," "financial closing," and the identification of "unusual trends." In this context, risk management was strongly embedded in systems, reporting routines, and validation mechanisms. The use of "structured dataflows," "validation checks," and standardised processes shows how formal risk control can be built directly into organisational systems and workflows.

However, the interviews also show that formal structures alone are not sufficient. Several respondents emphasised that risks often emerge through informal communication, everyday interactions, intuition, and practical experience. Int2 described how risks are identified not only through "regular internal meetings" and "management-level meetings," but also through "office discussions," "informal brainstorming sessions," and "discussions during lunch/coffee." This shows that even in organisations with structured communication channels, informal exchanges play an important role in detecting risks early.

Int8 expressed this even more directly by explaining that "important risks emerge informally," including through "casual conversations," "code reviews," and intuition when something "doesn't feel right." Int8 also connected this to the need to "create environment to raise concerns," suggesting that informal practices are not separate from risk management, but part of how early warning signals are recognised in practice.

The relationship between formal structures and informal practices was especially clear in Int5's interview. Although Int5 described a highly structured corporate environment with templates, regulations, KPIs, and formal risk documentation, he also pointed to a weakness in organisational learning. He noted a "missing formal post-evaluation," "no structured lessons learned process," and explained that "learning happens informally" through "internal discussions or gossip." This shows that formal systems may provide control and documentation, but do not automatically ensure that knowledge is systematically captured and transferred across projects.

In less formalised organisational contexts, risk management was even more dependent on the individual project manager. Int10 described "risk management not formalised at company level," "no company-wide guidelines," and risk being "handled individually by project managers." In this context, risk management was understood as a "professional responsibility" rather than a standardised organisational process. This decentralised approach allowed flexibility, but also meant that practices could vary depending on the experience and judgement of individual project managers.

Int1 provided a contrasting example where weak organisational structures contributed directly to risk. She described a "fragmented chain of command," "no clear reporting line," and "limited support for resolving risks." In her case, risks were often "identified after issues occur," indicating a more reactive environment where the absence of structured guidance made risk management dependent on individual problem-solving rather than systematic anticipation.

Organisational structure also influenced escalation and decision-making. Int2 described a clear escalation pattern where issues are "first addressed by individual," then go "to supervisor first," and are escalated "to head if unresolved." At the same time, Int2 also noted that team members "provide input but not final decision," while the "lead project manager makes final decisions." This indicates that structured organisations may distribute responsibility and input across teams, while still maintaining centralised decision authority.

Similarly, Int6 described how "project manager handles day-to-day risks," while "higher-level manager [is] involved in decisions" and risks beyond the project manager's authority are escalated. This distinction between operational and strategic risk responsibility shows how formal governance structures can clarify who is responsible for different types of risks. However, Int6 also noted that "companies differ in project and risk approaches," meaning that the effectiveness of such structures depends strongly on organisational maturity, culture, and available tools.

Overall, the findings show that risk management practices are shaped by the interaction between formal organisational structures and informal human practices. Formal systems such as risk matrices, documentation procedures, escalation mechanisms, reporting tools, and validation processes provide consistency and control. However, the interviews also show that informal discussions, intuition, experience, communication, and organisational culture remain essential for identifying risks that may not yet be visible in formal systems. Across the interviews, effective risk management therefore appeared not as purely formal or informal, but as a combined process in which structured systems are complemented by practical judgement and everyday communication.

4.4 International and Contextual Complexity

The analysis shows that international and contextual factors play a significant role in shaping how risks are perceived and managed across project environments. Across the interviews, respondents consistently described risk as something that is influenced not only by internal project conditions, but also by the broader environment in which the project takes place. These contextual factors include political and regulatory conditions, cultural differences, stakeholder behaviour, time zones, regional instability, logistical restrictions, and organisational structures.

One of the clearest patterns in the data is that risks vary depending on geographical and institutional context. Int10, who works in telecommunications projects, described a clear distinction between more stable and less stable environments, referring to "no major risks within EU" but "greater risks outside EU." This was linked to "frequent changes in conditions,"

“travel risks in certain countries,” and the need to monitor “restrictions on delivery and operations.” Similarly, Int6 emphasised that “risks vary significantly by country” and that high-risk environments may require “daily check-ins, emergency procedures” and “movement restrictions.” These examples show that risk is not perceived as uniform across projects, but as strongly shaped by the external environment in which the project is implemented.

Political and regulatory conditions were also repeatedly identified as important sources of contextual risk. Int3 explained that “government regulations influence projects,” while “government policy changes affect projects” and may require organisations to “redesign project activities.” In the same interview, environmental factors were also linked to risk, with Int3 noting that “climate affects timelines,” “rainy season stops construction,” and that planning must be aligned with the local environment. Int7 provided another example from a high-risk project in Nigeria, where risks included “corruption,” “fraud or misuse of funds,” and “stakeholder influence risk.” Together, these findings show that international project risk often emerges from a combination of political, institutional, environmental, and stakeholder-related conditions.

External disruptions also appeared as an important part of contextual complexity. Several respondents referred to COVID-19 as an example of how unexpected external events can disrupt project implementation. Int3 described the pandemic as “completely unexpected,” noting that it “affected all projects” and was “not forecasted in [the] risk matrix.” The response required adaptation, including the need to “shift to remote work,” “revise approach with client,” and “shift to online delivery.” Int10 similarly connected COVID-19 to practical execution risks, including blocked access to customer sites, “testing and validation” constraints, and delays in project finalisation. These examples show that international project risk often requires flexibility and adaptation when external conditions change unexpectedly.

The analysis also shows that geographically distributed work creates specific coordination risks. Int8 described international projects as “more complex” due to “managing communication across cultures,” “different time zones,” and the fact that “organizational structures differ.” Int8 also noted that when the “client, team, [and] users” are located in different regions, “communication must be structured,” dependencies must be “carefully managed,” and “better documentation [is] required.” Int9 similarly referred to “time zones slow communication,” “different ways of working,” and “different definitions/standards” as factors that create “risk of misalignment” and “risk of delays.” These findings demonstrate that international complexity is not only about external instability, but also about the practical difficulty of coordinating work across locations, teams, and organisational boundaries.

Cultural differences further influenced how risks were perceived and communicated. Int3 stated that “understanding cultural context [is] essential,” and that the “local environment influences risk.” Int8 provided a more communication-focused explanation, noting that culture affects “communication about risks,” including differences between “direct vs indirect communication styles.” Int8 also highlighted that in some contexts, “risk reporting [is] seen as confrontational,” while “hierarchical environments inhibit reporting.” Int1 also emphasised the importance of being “mindful of tone and cultural expectations,” especially where “language

barriers affect understanding" and "explicit communication [is] needed." These examples show that culture affects not only interpersonal communication, but also whether risks are reported early, how they are interpreted, and how openly they are discussed.

Stakeholder dependence was another recurring element of contextual complexity. Int2 described several risks connected to external actors, including "staff changes on client side," "delayed client feedback," "power struggle between stakeholders," and "misalignment of expectations." Int7 similarly described stakeholder-related risks in terms of "stakeholders frustrated with delays," "accusations of causing delays," and the need to adapt communication style because "stakeholders expect respect." These examples show that risk management in international projects extends beyond internal planning and requires continuous engagement with external stakeholders whose expectations, behaviour, and decisions cannot be fully controlled by the project manager.

The interviews also show that contextual complexity is not experienced in exactly the same way by all respondents. For Int4, risks were strongly connected to external and regional factors, including "political, financial, technological, and operational domains" and the importance of "regional variation and local context." In contrast, Int1 emphasised internal organisational conditions as a source of contextual complexity, including a "fragmented chain of command," "no clear reporting line," and "limited support for resolving risks." These differences suggest that while contextual complexity was a consistent theme across the interviews, the specific form it took depended on the respondent's organisational environment, sector, and project experience.

4.5 Communication, Culture, and Relational Risk

The analysis shows that communication, cultural factors, and relational dynamics play a central role in how risks emerge and are managed in project environments. Across the interviews, respondents consistently described risks not only as technical, financial, or external events, but also as issues that arise through interaction between individuals, teams, clients, beneficiaries, and other stakeholders. In this sense, risk management was strongly connected to how information is shared, interpreted, escalated, and acted upon within project settings.

One of the most frequently mentioned sources of risk was miscommunication or incomplete communication. Int1 described several risks connected to unclear information flows, including "received incorrect information," "inadequate handover process," and an "information dump without context." These communication issues were linked to "delayed escalation response," "lack of responsibility," and an avoidable situation where the "project requires extension." This shows how communication breakdowns can escalate into wider project risks, especially when responsibilities and reporting lines are unclear.

A similar pattern appeared in Int2's interview, where risk was strongly linked to information flow between project actors. Int2 referred to "team leader as communication bridge," "PM communicates on contractual matters," and the need for "regular discussions with team." At

the same time, Int2 also highlighted risks connected to “delayed client feedback,” “internal team misalignment,” and “misalignment of expectations.” These examples show that communication is not only a support function in project management, but a central mechanism through which risks are either reduced or amplified.

The importance of communication was also visible in more technical project environments. Int8 explained that “transparency and open communication” are important because “hiding risks makes things worse.” Int8 further emphasised the need to “discuss risks with team and client,” “raise concerns early,” and create a “culture of openness” where “people feel comfortable speaking up.” This suggests that early communication of uncertainty is perceived as a practical risk control mechanism, particularly in complex project settings where risks may not be immediately visible through formal systems.

Cultural differences further influenced how risks were communicated and interpreted. Int8 explained that “culture affects communication about risks,” particularly through “direct vs indirect communication styles.” The interview also highlighted that “risk reporting [may be] seen as confrontational” and that “hierarchical environments inhibit reporting.” These statements show that cultural norms can affect whether risks are openly raised or remain implicit, which in turn influences how early they can be identified and addressed.

Int1 similarly emphasised the need to be “mindful of tone and cultural expectations” and to “avoid assumptions in communication.” She also pointed to “language barriers” and the need for “explicit communication,” especially in international project environments where misunderstandings may arise from translation or cultural differences. These findings show that communication risk is not limited to whether information is exchanged, but also involves how messages are framed, interpreted, and understood across cultural contexts.

Relational dynamics between stakeholders also emerged as an important source of risk. Int7 provided a clear example in which an “email describing low standards” was “accidentally copied [to the] beneficiary,” after which “stakeholders focused on one phrase,” “felt disrespected,” and the situation created a “risk of team replacement.” Int7 explicitly described this as “risk not technical but relational,” highlighting the “importance of tone in communication.” This example demonstrates how even a relatively small communication issue can become a reputational or contractual risk when stakeholder relationships are sensitive.

Stakeholder pressure and power dynamics also shaped risk management. Int7 described situations where stakeholders were “frustrated with delays,” made “accusations of causing delays,” and where the project team had to balance pressure to act quickly with the need to maintain compliance and control. Int2 also identified relational risks such as “power struggle between stakeholders,” “passive client vs active beneficiary,” and “client too involved in details.” These examples indicate that project risks can emerge from conflicting expectations, unclear authority, or stakeholder behaviour that cannot be fully controlled through formal procedures alone.

Psychological safety and openness were also important in explaining how risks become visible. Int8 stated that “false alarms [are] acceptable,” and connected this to “psychological safety for risk reporting” and “early warning advantage.” Int8 also described “important risks [that] emerge informally” through “casual conversations,” “code reviews,” and intuition when something “doesn’t feel right.” This suggests that organisations that encourage early reporting and informal discussion may be better able to detect weak signals before they become serious project problems.

Coordination across teams was another recurring communication-related issue. Int9 described risks arising from “time zones,” “different ways of working,” and “different definitions/standards,” which can create “risk of misalignment” and “risk of delays.” Int9 therefore emphasised the importance of “documentation,” “clear definitions and processes,” and “regular communication and check-ins” to “reduce ambiguity.” Similarly, Int8 noted that in distributed international work, “communication must be structured,” “dependencies carefully managed,” and “better documentation [is] required.”

4.6 Role of Data, Systems, and Technology in Risk Management

The analysis shows that data, systems, and digital tools play an important role in how risks are identified, monitored, and managed across project environments. However, the role of these tools differs significantly depending on the organisational context, the type of project, and the level of technological maturity within the organisation. Across the interviews, digital tools were not generally described as replacing human risk management practices, but rather as supporting visibility, monitoring, documentation, coordination, and early identification of potential issues.

The strongest example of data-driven risk management appears in Int9’s interview. Working in a reporting and data-focused project environment, Int9 described risk as closely connected to “data quality, timelines, decision-making,” adding that “small data issues can have big impact.” Risk management in this context was therefore strongly embedded in data accuracy, system reliability, and reporting quality. Int9 explained that risks are identified through “data validation processes,” “regular reporting cycles,” “financial closing,” and the ability to “identify unusual trends” or “flag inconsistencies.” These statements show that in highly data-driven environments, risk identification can be built directly into reporting processes and system checks.

Digital tools were also used to improve transparency and visibility. Int9 referred to the use of “SQL, Power BI, Microsoft Fabric,” “automated data pipelines,” and “dataflows processing large datasets.” These systems helped with “visualisation,” “identify anomalies,” improving “dashboards,” and allowing “faster identification of risks.” In this context, systems support risk management by making deviations and inconsistencies more visible before they develop into larger problems. This finding differs from interviews in less data-driven environments, where risk management relied more strongly on communication, experience, and informal escalation.

A similar, although less technically embedded, pattern appears in Int2's interview. Int2 described the use of digital tools for "resources," "monitor budget usage," "identify over/underuse," "track expenses and margins," and monitor deliverables through a "tracking system." Digital systems were also connected to practical project control through "Gantt-style planning," "deadline notifications," and tracking "approvals for payments." In this case, digital tools supported risk management by improving project visibility and helping project managers monitor capacity, budget, deadlines, and contractual compliance.

Int1 also described the potential value of more integrated digital systems, particularly in contexts where poor systems themselves created risk. In her interview, risk was linked to "outdated budgeting systems," "fragmented chain of command," and "risks not systematically identified." At the same time, she identified the future potential of "automated dashboards and tracking," "centralised project information systems," and "process standardisation." This shows that digital systems were not only viewed as technical tools, but also as potential solutions to organisational weaknesses, especially where fragmented structures made risks harder to identify and manage consistently.

In more technical project environments, digital and system-based approaches were also connected to documentation and structured control. Int8 described the use of traditional project tools such as "Jira" and "Confluence," as well as "tools for tracking and risk registers." These supported formal documentation and monitoring, but Int8 also emphasised that tools alone were not enough, since "important risks emerge informally" through conversations, code reviews, and intuition. This indicates that even in tool-supported environments, systems function as part of a broader risk management process that still depends on human interpretation and communication.

The interviews also show that digital tools and systems are especially useful when they support standardisation and reduce ambiguity. Int9 explained that risk is managed through "clear definitions and processes," "documentation," "regular communication and check-ins," and efforts to "reduce ambiguity." This was particularly important in international and cross-functional settings, where different teams may use different definitions, standards, or ways of working. In this sense, systems and documentation do not only support technical control, but also help align understanding between distributed teams.

However, the analysis also shows that systems and digital tools have limitations. They can identify deviations, inconsistencies, or missing information, but they do not automatically explain the meaning or importance of these findings in a broader project context. Int9 described the need to "investigate further manually," "consider business context," and "combine data insights with experience." This indicates that data-driven risk identification still requires human interpretation before it can become meaningful for decision-making.

This point also appears in Int5's interview, where AI and data tools were seen as useful only under certain conditions. Int5 described AI-supported analysis as "useful with existing data" and able to "help identify inconsistencies," but also stated that outputs are "not relied on fully" and must be filtered through experience. Similarly, Int10 argued that AI and digital tools may

support “large data analysis” and help “identify patterns,” but that “human must review outputs” and “complex work requires human input.”

Overall, the findings show that data, systems, and digital tools support risk management by improving visibility, documentation, monitoring, and early detection. Their role is especially strong in data-driven and structured organisational environments, where risk can be identified through validation checks, dashboards, reporting cycles, and system-based controls. However, the interviews also consistently show that technological systems do not replace managerial judgement. Their usefulness depends on how they are embedded into organisational processes and how their outputs are interpreted by project managers. Across the interviews, digital tools therefore appear as supporting mechanisms within risk management rather than independent systems of risk control.

4.7 Use of AI in Project Risk Management

The analysis shows that the use of artificial intelligence in project environments varies significantly across organisations, both in terms of how frequently it is used and what types of tasks it supports. Across the interviews, AI was generally not described as a fully integrated decision-making system for project risk management. Instead, respondents positioned AI as a tool that can support communication, documentation, research, information processing, forecasting, or analytical reflection. The extent of AI use depended strongly on organisational policies, technological maturity, individual familiarity with AI tools, and the type of project environment in which the respondent worked.

In several interviews, AI was described primarily as a tool for administrative and communication-related support. Int2 referred to “AI for drafting communication,” “AI for basic research,” “AI for reviewing documents,” “AI for extracting key information,” and “AI for generating solutions.” These uses were connected to practical benefits such as “lightens workload,” “faster responses,” “improves tone of communication,” and “reduces misunderstandings.” Similarly, Int1 described AI as useful for “recording meetings” and “summarising notes,” especially because it “helps capture information during meetings” and can support “deliverables accuracy.” In these cases, AI supports project work indirectly by improving efficiency and reducing the risk of missing information, rather than directly identifying or managing risks.

AI was also described as useful in proposal preparation, research, and early project stages. Int4 described AI as a “widely used operational support tool,” particularly in “communication, recruitment, and research.” It was also connected to “drafting,” “structuring,” and “preliminary research,” which improved “speed and productivity in proposal development.” Int6 similarly noted that AI is “mainly used in tendering” and for “drafting and information gathering,” while its use in direct risk management remained limited. This suggests that AI may influence risk management indirectly at the pre-project stage, for example by supporting research and proposal development, but it is still not treated as an independent risk management mechanism.

In other interviews, AI and data-driven tools were described in a more analytical way. Int3 referred to AI being used for "market research," to "verify cost assumptions," and to "compare rates with real-world data." He also described AI as potentially useful for "forecasting based on past data," "predict success rates and resource use," and "understand project evolution." Similarly, Int9 described AI and data-driven tools as useful for "large datasets," helping identify "hard-to-spot issues" and supporting the recognition of complex patterns. In these data-oriented contexts, AI contributes more directly to analytical support, particularly where large volumes of information need to be processed or where patterns are difficult to identify manually.

However, even where AI was described as analytically useful, respondents consistently emphasised that it does not replace human judgement. Int3 described AI as a "second opinion," an "objective perspective," and a way to "compare AI output with experience," but also stated that managers should "never rely 100% on AI" and should use it as a "complementary tool." Int8 used similar language, describing AI as a "sounding board," a tool that "challenges assumptions," and a "second pair of eyes." At the same time, Int8 stressed that "human judgment still essential" and that AI is "stronger in analysis than decisions." These interviews show a consistent pattern in which AI is valued for broadening perspectives and supporting reflection, but not for taking over decision-making responsibility.

The limitations of AI were particularly clear in relation to context, reliability, and complex project environments. Int2 noted that AI outputs are affected by "question framing," may be "inconsistent," and can have "difficulty with complex context." She also stated that "AI not used for final decisions," and that decisions still depend on "experience and judgement." Int6 similarly argued that projects are "complex and multifactorial," involving "technical, contractual, organisational, human factors," "different client behaviours," and variation within organisations. For this reason, she stated that AI "cannot replace human decisions" and that "human verification always needed."

Trust in AI was therefore conditional across the interviews. Int3 explained that trust depends on "source transparency," the need to "verify reliability of information," and the importance of "clear references." Int9 connected trust to "data quality," "understanding tool logic," and whether outputs are consistent, while also emphasising the need to "question unclear results" and "validate inconsistent outputs." Int10 also raised concerns about accuracy, noting that "AI answers may not be accurate," that responses need to be analysed, and that AI "must be cross-checked." Across these interviews, trust was not presented as automatic, but as dependent on transparency, data quality, user competence, and validation.

Organisational context also shaped how AI could be used in practice. Int10 described "AI use restricted in company," explaining that users "cannot input sensitive data," must rely on "generic inputs," and are limited to "approved tools." Int5 similarly explained that "AI use is individual, not organisational," with "no company-wide AI strategy" and usage depending on "individual choice." These examples show that AI adoption is not only determined by the usefulness of the technology itself, but also by organisational rules, data security concerns, and the level of institutional integration.

Several respondents also identified risks created by AI itself. Int5 warned that AI can be "unreliable with numbers," "can go in wrong direction," and may introduce "accuracy and precision concerns." He also stressed that "human oversight [is] essential" and that "AI without judgment creates problems." Int10 similarly highlighted the "danger in relying completely on AI" and the risk of reduced "critical thinking." These views show that AI is not only perceived as a tool for reducing risk, but also as a potential source of new risks if used without sufficient human evaluation.

4.8 AI and Risk Perception in Decision-Making

The analysis shows that while AI-supported tools are increasingly present in project environments, their influence on how risk is perceived and interpreted remains mostly indirect. Across the interviews, respondents did not describe AI as fundamentally changing their understanding of risk. Instead, AI was presented as a tool that supports reflection, provides additional perspectives, helps process information, and occasionally challenges assumptions. In this way, AI contributes to risk-related decision-making without replacing the role of managerial interpretation.

One of the clearest ways in which AI influences risk perception is by acting as an additional perspective or reflective support mechanism. Int8 described AI as a "sounding board," stating that it "challenges assumptions," "forces articulation of assumptions," and acts as a "second pair of eyes." At the same time, Int8 clearly stated that "human judgment still essential," showing that AI may support reflection but does not take over responsibility for interpreting risk. Similarly, Int3 described AI as a "second opinion" and an "objective perspective," while also emphasising the need to "compare AI output with experience" and "never rely 100% on AI."

This pattern also appeared in Int2's interview, where AI was described as something that may "trigger doubt" and be combined with "multiple inputs." However, Int2 also stated that AI is "not used for final decisions," and that decision-making still depends on "experience and judgement." This suggests that AI may influence the decision-making process by encouraging reconsideration or reflection, but it does not replace the project manager's own assessment.

A similar pattern appeared in Int10's interview. Int10 explained that AI answers must be compared with expectations and rejected if they do not fit the project context. He described the need to "analyse responses," "compare AI answers with expectations," and "reject answers if they don't fit." He also stated that AI "must be cross-checked" and compared its use to "consulting another person." This indicates that AI-generated insights are filtered through the project manager's existing knowledge, practical experience, and contextual understanding.

In more data-driven environments, AI and related tools appeared to have a stronger influence on the early recognition of risks by making patterns and inconsistencies more visible. Int9 described AI and data tools as useful for "large datasets," helping identify "hard-to-spot issues," and supporting the recognition of patterns that may not be obvious manually. Int5

similarly described AI as “useful with existing data,” able to “help identify inconsistencies,” and supportive of “follow-up questions.” These examples show that AI can contribute to risk perception by making certain signals more visible, particularly in structured or data-rich project environments.

However, even in these more analytical contexts, respondents consistently emphasised that AI-generated signals still require human interpretation. Int9 described the need to “investigate further manually,” “consider business context,” and “combine data insights with experience.” Int8 similarly explained that AI may “reveal blind spots,” but may also “miss context,” and that “differences trigger deeper analysis” rather than automatic acceptance. This shows that AI may contribute to identifying potential areas of concern, but the meaning and relevance of those signals remain dependent on human judgement.

The limitations of AI were especially visible in situations involving complex stakeholder relationships, cultural differences, internal politics, or strategic decisions. Int8 noted that AI “lacks contextual understanding,” that “internal politics [are] not captured,” and that “informal factors matter.” Int7 similarly stated that AI “cannot fully grasp context,” particularly in relation to “complex stakeholder discussions,” and that “human judgement [is] required.” Int6 also argued that projects are “complex and multifactorial,” involving “technical, contractual, organisational, human factors,” “different client behaviours,” and “human factors,” which require “judgment and adaptability.” These findings indicate that AI has less influence on risk perception in areas where uncertainty is relational, political, or highly contextual.

Across the interviews, AI was therefore not perceived as redefining risk or replacing the manager’s interpretation of uncertainty. Instead, it was positioned as one input among several. Int8 explicitly described AI as “one input among many” and explained the process as forming one’s “own perspective first,” then comparing “AI vs own thinking.” Int2 similarly referred to combining “multiple inputs,” while Int10 described AI as comparable to “consulting another person.”

4.9 Trust, Limitations, and Human–AI Interaction in Decision-Making

The analysis shows that trust in AI is a central factor shaping how AI-supported tools are used in project environments, particularly in relation to risk management and decision-making. Across the interviews, trust in AI was generally described as conditional rather than automatic. Respondents did not reject AI as a tool, but they consistently emphasised that AI-generated outputs must be checked, interpreted, and evaluated before they can be used in project decisions. This pattern appeared across respondents with both high and limited levels of AI exposure.

One of the most frequently mentioned concerns was the accuracy and reliability of AI-generated outputs. Int10 expressed concern that AI “may generate answers just to respond,” and also noted that AI answers “may not be accurate” and therefore require analysis and verification. In the same interview, Int10 stated that AI “must be cross-checked” and that users

need to “compare AI answers with expectations” before accepting them. Int5 raised similar concerns, describing AI as “unreliable with numbers,” warning that it “can go in wrong direction,” and highlighting “accuracy and precision concerns.” These statements show that respondents were aware of AI’s usefulness, but also cautious about treating its outputs as reliable without further validation.

Trust was also closely linked to transparency and data quality. Int3 explained that trust in AI “depends on source transparency,” that users need to “verify reliability of information,” and that “clear references increase trust.” Int9 similarly connected trust to “data quality,” “understanding tool logic,” and consistency over time, while also emphasising the need to “question unclear results” and “validate inconsistent outputs.” Int2 also highlighted that the “quality depends on input quality,” and that trust depends on “understanding tool” and knowing its “limitations.” Across these interviews, trust was not presented as a general attitude toward AI, but as something shaped by the quality of the data, the transparency of the output, and the user’s ability to understand how the tool works.

Organisational context also shaped trust and use. In some cases, AI use was restricted because of confidentiality and data protection concerns. Int10 described an environment where “AI use [is] restricted in company,” where employees “cannot input sensitive data” and must use “generic inputs” or “approved tools.” Int5 similarly noted that AI use was “individual, not organisational,” with “no company-wide AI strategy” and usage depending on “individual choice.” These examples show that AI adoption is not determined only by individual willingness or technical usefulness, but also by organisational policies, data security concerns, and the extent to which AI is formally integrated into company systems.

The limitations of AI were especially clear in relation to complex and context-dependent project environments. Int6 described projects as “complex and multifactorial,” involving “technical, contractual, organisational, human factors,” “different client behaviours,” and variation across organisations. For this reason, she stated that AI “cannot replace human decisions” and that “human verification always needed.” Int8 made a similar point by noting that AI “lacks contextual understanding,” that “internal politics [are] not captured,” and that “informal factors matter.” Int7 also stated that AI “cannot fully grasp context,” particularly in relation to “complex stakeholder discussions,” and therefore “human judgement [is] required.” These findings show that AI was considered more useful in structured and data-driven tasks than in situations requiring contextual interpretation, stakeholder sensitivity, or political judgement.

Several respondents also identified risks created by AI itself. Int10 warned about the “danger in relying completely on AI” and connected this to the risk of reduced “critical thinking.” Int5 similarly argued that “AI introduces new risks,” including “accuracy and precision concerns” and the fact that errors may be “difficult to detect.” He also stressed that “human oversight [is] essential” and that “AI without judgment creates problems.” These statements show that AI was not only seen as a tool for reducing risk, but also as a possible source of new risk if used without sufficient critical evaluation.

Despite these concerns, respondents did not generally view AI negatively. Instead, AI was consistently positioned as a tool that can support human judgement when used carefully. Int3 described AI as a "second opinion" and a "complementary tool," while also stressing that project managers should "never rely 100% on AI." Int8 described AI as "one input among many," explaining that project managers should "form own perspective first" and then "compare AI vs own thinking." Int10 also compared AI to "consulting another person," meaning that AI-generated outputs may be considered, but should not automatically be accepted as correct.

The interaction between human judgement and AI therefore follows a consistent pattern across the interviews. Project managers first rely on their own understanding of the project situation, then use AI to gather input, identify possible blind spots, or test assumptions, and finally evaluate whether the AI-generated output fits the specific project context. Int2 captured this balance by describing how AI may "trigger doubt," but still needs to be combined with "multiple inputs," "experience and judgement," and, where necessary, validation with supervisors or colleagues. Int9 similarly described the need to "investigate further manually," "consider business context," and "combine data insights with experience."

4.10 Summary of Key Findings

This chapter has presented the analysis of how project managers perceive and manage risk, and how AI-supported tools are positioned within these processes across different organisational and international contexts. The findings show that risk is understood as a complex and multi-dimensional concept shaped by technical, organisational, contextual, and relational factors. While respondents commonly associated risk with threats to project delivery, timelines, resources, and performance, the way risk was interpreted varied depending on the project environment, organisational setting, sector, and professional experience of the interviewee.

The analysis further shows that risk management practices differ significantly across organisations. Some respondents described structured and formalised approaches, including risk matrices, documentation requirements, reporting cycles, validation processes, and escalation mechanisms. Others described more decentralised or reactive environments where risk management depended more strongly on individual judgement, informal communication, and practical experience. Across the interviews, however, risk management was generally presented as a continuous and evolving process rather than a one-time activity. Early-stage assessment, particularly during proposal, bidding, pre-sales, or tender phases, also appeared as an important part of how risks are anticipated and managed before projects formally begin.

Organisational context emerged as a strong influence on both risk perception and risk management practice. Factors such as governance structures, organisational maturity, communication routines, reporting lines, and decision-making authority shaped how risks were identified, escalated, and addressed. At the same time, international and contextual complexity introduced additional challenges, including regulatory differences, political uncertainty, cultural expectations, stakeholder dynamics, time zones, and coordination across distributed

teams. These factors increased uncertainty and required project managers to adapt their approaches to different project and country contexts.

The findings also highlight communication, culture, and relational dynamics as central mechanisms of risk control. Risks frequently arose from misalignment, unclear communication, stakeholder pressure, cultural differences, and incomplete information flows rather than from purely technical problems. Across several interviews, effective risk management was connected to transparency, regular communication, documentation, openness, and the ability to raise concerns early. This indicates that risk management depends not only on formal procedures, but also on the quality of interaction between project actors.

In relation to technology, the analysis shows that data, systems, and digital tools play a growing role in supporting risk management. These tools improve visibility, enable earlier detection of deviations, support documentation, and help structure project monitoring. In data-driven and system-based environments, risk management was often embedded into validation processes, dashboards, reporting tools, and standardised workflows. However, the findings also show that such systems require human interpretation. Tools may identify anomalies, inconsistencies, or patterns, but project managers still need to assess their relevance within the broader project context.

With regard to artificial intelligence, the findings indicate that AI use in project risk management is still developing and varies across organisational contexts. AI was mainly used for administrative support, information processing, drafting, summarisation, idea generation, research, forecasting, and pattern recognition. Its influence on risk perception was generally indirect, as it helped respondents reflect, compare perspectives, identify possible blind spots, or process larger volumes of information. However, AI was not described as fundamentally changing how project managers understand risk or as replacing managerial decision-making.

Trust in AI was generally conditional and shaped by factors such as data quality, transparency, consistency, accuracy, source reliability, organisational restrictions, and the user's ability to understand and validate the output. Respondents repeatedly emphasised the need to critically evaluate AI-generated outputs, particularly in complex or context-sensitive situations. AI was seen as more useful in structured, data-driven, or repetitive tasks, while its limitations were clearer in situations involving stakeholder relationships, cultural differences, political uncertainty, or strategic judgement.

5 Discussion

5.1 Risk Perception as a Contextual and Interpretive Process

The findings of this study support the idea that risk perception in project environments extends beyond purely rational or technical calculations. While traditional project risk management frameworks often present risk as something that can be identified, measured, and controlled through structured processes, the interviews reveal that project managers perceive and interpret risk in much more contextual and dynamic ways. Across the analysis, risk was frequently associated not only with measurable threats to time, cost, or scope, but also with uncertainty related to communication, stakeholder behaviour, organisational dynamics, and external contextual factors.

This finding aligns with broader critiques of rational risk management models presented in the literature. Aven (2015) argues that risk cannot be fully reduced to probability calculations because uncertainty is often incomplete, ambiguous, and difficult to quantify. Similarly, Power (2007) criticises the growing tendency of organisations to formalise and standardise risk management processes while overlooking the social and interpretive dimensions of uncertainty. The findings of this thesis reflect these critiques, as respondents repeatedly described situations where risks emerged from changing stakeholder expectations, communication breakdowns, or contextual complexity rather than from clearly measurable events.

The analysis also supports the argument that risk perception is strongly influenced by individual interpretation and experience. Slovic (1987) emphasises that risk is not perceived objectively, but is shaped by psychological, social, and cultural influences. This perspective was clearly reflected in the interviews, where respondents often relied on intuition, previous experience, or informal judgement when evaluating uncertainty. In several cases, project managers described recognising risks through indirect signals, such as communication issues, stakeholder hesitation, or situations where “something did not feel right.” These findings indicate that risk perception involves interpretive judgement rather than purely analytical calculation.

The role of human judgement observed in the findings also connects closely to behavioural decision theory. Kahneman and Tversky (1979) argue that decision-making under uncertainty is influenced by subjective perceptions and cognitive biases rather than fully rational evaluation. Similarly, March and Shapira (1987) suggest that managers often perceive risk through the lens of experience, organisational expectations, and potential consequences rather than through statistical reasoning alone. The interviews conducted in this study support this perspective, as respondents frequently discussed risk in practical and contextual terms rather than through formal probability assessments. Even in organisations with structured risk management systems, respondents emphasised that managerial interpretation remained essential in understanding the significance of identified risks.

Another important aspect emerging from the findings is the relational and communicative nature of risk. Several respondents identified communication problems, stakeholder misalignment, and coordination difficulties as central sources of uncertainty in projects. This reflects Weick's (1995) concept of sensemaking, which views organisational actors as continuously interpreting and constructing meaning in uncertain environments. From this perspective, risk is not simply discovered objectively but is actively interpreted through interaction and communication. The interviews strongly support this view, particularly in international project environments where respondents described the importance of contextual understanding, alignment between stakeholders, and ongoing interpretation of changing situations.

The findings therefore suggest that project risk management cannot be understood solely as a technical process based on formal tools and procedures. While structured frameworks such as PMBOK provide important mechanisms for identifying and monitoring risks, the practical interpretation of uncertainty remains highly dependent on organisational context, communication processes, and managerial judgement. Risk perception emerges not as a static or objective assessment, but as an ongoing interpretive process shaped by experience, interaction, and contextual complexity.

This interpretation is particularly important in relation to the broader research question of the thesis. Since risk perception itself is deeply contextual and human-centred, the role of AI in supporting project risk management becomes inherently limited by the complexity of human interpretation. The findings indicate that AI may support information processing and analytical tasks, but the interpretation and contextual understanding of risk remain primarily dependent on human judgement. This provides an important foundation for the following sections, which further discuss how organisational environments and AI-supported systems interact within project risk management processes.

5.2 Organisational and International Context as Determinants of Risk Management

The findings of this study show that risk management practices are strongly shaped by organisational and international context. Although project management literature often presents risk management as a structured and standardised process, the interviews reveal significant variation in how risks are identified, interpreted, and managed across organisations. These differences were particularly visible in relation to organisational structure, governance processes, communication practices, and the international environments in which projects operate.

One of the clearest patterns emerging from the analysis is the distinction between structured and decentralised approaches to risk management. Respondents working in larger or more mature organisations often described formalised systems involving standardised reporting structures, documentation procedures, validation mechanisms, and defined escalation processes. In these environments, risk management was integrated into organisational governance and supported by formal systems and routines. This aligns with the structured perspective of project risk management discussed in frameworks such as PMBOK (PMI, 2021)

and the work of Hillson and Simon (2020), where risk management is treated as a systematic organisational process.

At the same time, the findings indicate that many organisations rely heavily on informal practices and individual judgement despite the existence of formal systems. Several respondents described risk management as dependent on the experience and interpretation of project managers rather than solely on organisational procedures. In some cases, risk management was not fully formalised at organisational level, resulting in greater flexibility but also increased variation between projects. This reflects the argument made in the literature that risk management practices are shaped not only by formal frameworks, but also by organisational maturity, routines, and culture.

The findings also highlight the importance of organisational communication and coordination structures in shaping project risk. Across multiple interviews, respondents identified communication breakdowns, unclear responsibilities, and stakeholder misalignment as important sources of uncertainty. In larger organisations, respondents frequently referred to delays caused by multiple decision-making layers or the need for alignment across departments and regions. These findings support the view that organisational complexity itself can become a source of project risk, particularly in environments where coordination is difficult or responsibilities are fragmented.

International and contextual complexity further intensified these challenges. Respondents consistently described how projects operating across different countries and institutional environments faced additional uncertainty related to political conditions, regulations, cultural differences, and external stakeholder expectations. In several interviews, risks associated with operating outside stable European environments were described as more difficult to predict and manage due to changing local conditions and institutional instability. These findings strongly reflect the international management and institutional perspectives discussed in the literature review, particularly the idea that organisational practices and risk environments are shaped by broader institutional and contextual conditions.

Cultural differences also appeared to influence communication patterns and approaches to risk. Respondents described situations where teams in different regions communicated differently, interpreted project expectations differently, or varied in their willingness to raise concerns and discuss uncertainty openly. In international project environments, this created additional complexity in coordinating teams and ensuring alignment between stakeholders. These findings support earlier discussions in the literature regarding the influence of national and organisational culture on risk perception and managerial behaviour.

Another important finding is that international complexity increases the importance of relational and adaptive capabilities within project management. Rather than relying exclusively on structured procedures, respondents often emphasised the need for flexibility, communication, and contextual understanding when operating in uncertain international environments. This suggests that formal risk management systems alone are insufficient in

highly dynamic project settings. Instead, project managers must continuously interpret changing conditions and adapt their responses accordingly.

The findings therefore indicate that risk management practices cannot be understood independently of organisational and international context. While structured frameworks provide an important foundation, the practical management of risk depends heavily on organisational maturity, governance structures, communication processes, and the complexity of the environments in which projects are conducted. This is particularly important in international projects, where uncertainty is amplified by institutional, cultural, and contextual variation.

In relation to the research question, these findings suggest that the utilisation of AI-supported risk management tools is also shaped by organisational and contextual conditions. Since organisations differ significantly in terms of structure, communication practices, and technological maturity, the adoption and practical use of AI systems vary accordingly. This reinforces the idea that AI-supported risk management cannot be separated from the broader organisational environments within which project managers operate.

5.3 AI as a Supportive Rather than Autonomous Decision-Making Tool

The findings of this study indicate that artificial intelligence currently functions primarily as a supportive tool within project risk management rather than as an autonomous decision-making mechanism. Across the interviews, respondents consistently described AI as something that assists project managers by improving efficiency, processing information, generating ideas, or identifying patterns, while the final interpretation and decision-making responsibility remained human-centred. This finding is particularly significant in relation to the research question, as it suggests that project managers utilise AI mainly to support existing risk management practices rather than to fundamentally transform them.

One of the clearest patterns in the analysis is that AI is most commonly used for administrative and analytical support tasks. Respondents frequently referred to the use of AI tools for drafting emails, summarising information, structuring documents, conducting quick research, or supporting proposal development. In more technically oriented environments, AI-supported systems were also used to identify anomalies, process large datasets, and improve visibility within reporting processes. These findings align with the broader literature on AI adoption in project management, which emphasises AI's growing role in automating repetitive tasks and supporting data-driven analysis.

However, despite the increasing use of AI tools, the findings show that respondents rarely viewed AI as capable of independently managing project risk. Instead, AI was consistently positioned as a tool that provides input into decision-making processes rather than replacing managerial judgement. Several respondents described AI as a "second opinion" or a mechanism for exploring additional perspectives. In practice, this meant that AI-supported outputs were reviewed, interpreted, and evaluated alongside human experience and contextual

understanding before decisions were made. This strongly supports the idea of augmentation rather than automation discussed in the literature review.

The findings also demonstrate that the usefulness of AI depends heavily on the structure and predictability of the task being performed. Respondents generally viewed AI as more effective in structured, data-driven environments where information could be processed systematically. For example, AI-supported systems were described as useful for identifying inconsistencies in datasets, improving reporting visibility, or detecting measurable anomalies. In these situations, AI contributed positively to early risk identification and information processing.

At the same time, respondents consistently expressed reservations regarding AI's ability to operate effectively in more complex and context-dependent situations. Tasks involving stakeholder management, communication, political sensitivity, or rapidly changing project environments were generally viewed as less suitable for AI-supported decision-making. These findings suggest that while AI performs relatively well in structured and measurable environments, its usefulness decreases when uncertainty becomes highly contextual or relational.

Another important finding is that the adoption and use of AI varied significantly between organisations. Some respondents described relatively advanced use of AI-supported systems and analytical tools, while others reported only minimal or experimental use of AI technologies. In several cases, organisational policies related to confidentiality and data protection restricted the use of AI systems in practical project settings. This indicates that AI utilisation is shaped not only by technological capability, but also by organisational maturity, governance structures, and institutional attitudes toward technology adoption.

The findings therefore support a more cautious and nuanced understanding of AI in project risk management. While some literature presents AI as having transformative potential within project environments, the interviews conducted in this study suggest that current practical use remains relatively limited and heavily dependent on human oversight. AI appears to function primarily as a complementary support mechanism that assists project managers in processing information and reflecting on decisions rather than independently managing uncertainty.

This interpretation is particularly important in relation to the broader theoretical discussion surrounding decision-making and risk perception. Since project risk often involves ambiguity, contextual interpretation, and interpersonal dynamics, the findings suggest that fully autonomous AI-supported risk management remains difficult in practice. Instead, the interaction between human judgement and technological support emerges as the dominant model within the analysed project environments.

5.4 Human Judgement, Trust, and the Limitations of AI in Complex Project Environments

The findings of this study indicate that human judgement remains central to project risk management despite the increasing availability and use of AI-supported tools. Although respondents acknowledged the usefulness of AI in supporting information processing and analytical tasks, they consistently emphasised that AI-generated outputs require interpretation, validation, and contextual assessment before they can be incorporated into decision-making processes. This suggests that trust in AI within project environments is conditional rather than absolute and that project managers continue to rely heavily on their own experience and judgement when managing uncertainty.

One of the clearest findings in the analysis is that trust in AI is strongly linked to transparency, consistency, and contextual relevance. Respondents generally expressed greater confidence in AI systems when dealing with structured and measurable tasks, particularly where outputs could be verified through existing knowledge or data. However, confidence decreased significantly in situations involving ambiguity, stakeholder dynamics, or rapidly changing project conditions. Several respondents specifically highlighted concerns regarding inaccurate or misleading AI-generated outputs, particularly in cases where systems produced convincing answers without sufficient contextual understanding. These findings support broader discussions in the literature regarding the importance of perceived reliability and trust in technology adoption.

The findings also reinforce behavioural and interpretive perspectives on decision-making discussed in the literature review. As argued by March and Shapira (1987), managerial decision-making is shaped not only by formal analysis but also by experience, intuition, and organisational context. Similarly, Slovic (1987) emphasises that perceptions of uncertainty are influenced by subjective interpretation rather than objective calculation alone. The interviews conducted in this study strongly support these perspectives, as respondents consistently described relying on personal judgement when evaluating whether AI-generated outputs were reasonable, useful, or relevant to the specific project context.

Another important finding is that AI appears to struggle particularly in environments characterised by high contextual complexity. Across the interviews, respondents repeatedly described international projects as involving political uncertainty, communication challenges, stakeholder sensitivity, and rapidly changing external conditions. In these environments, project managers viewed contextual interpretation and relational understanding as essential aspects of risk management that could not easily be replicated through AI-supported systems. This finding aligns closely with Weick's (1995) concept of sensemaking, which emphasises that individuals continuously interpret and construct meaning in uncertain organisational environments. The findings suggest that AI may support access to information, but the interpretation of meaning and relevance remains dependent on human actors.

The analysis further indicates that the use of AI may itself introduce new forms of risk within project environments. Several respondents expressed concerns regarding over-reliance on AI-generated outputs and the possibility that excessive dependence on automated systems could reduce critical thinking or lead to false confidence in decision-making. In this sense, AI becomes both a tool for managing uncertainty and a potential source of uncertainty itself. These concerns were particularly evident in situations where respondents questioned whether project managers might gradually accept AI outputs without sufficiently challenging or validating them.

At the same time, the findings do not suggest resistance toward AI as such. Most respondents viewed AI positively and recognised its practical benefits, particularly in improving efficiency and reducing administrative workload. However, the findings indicate that respondents generally viewed AI as most useful when operating alongside human expertise rather than independently from it. Human oversight was consistently described as necessary for validating outputs, interpreting context, and balancing technical information with organisational and stakeholder considerations.

These findings contribute directly to the broader research question of the thesis by demonstrating that AI-supported risk management remains fundamentally dependent on human-centred interpretation and judgement. While AI can assist project managers by expanding access to information and improving analytical support, the findings suggest that complex project environments still require human actors to interpret uncertainty, evaluate context, and make final decisions. This reinforces the broader conclusion emerging throughout the thesis that project risk management remains as much a social and interpretive process as a technical one.

5.5 Theoretical and Practical Implications of AI-Supported Risk Management

The findings of this study contribute to the growing discussion surrounding the role of artificial intelligence in project risk management by highlighting the continued importance of human interpretation, organisational context, and contextual complexity in decision-making processes. While much of the existing literature emphasises the transformative potential of AI within project management, the findings presented in this thesis suggest a more nuanced reality in which AI primarily functions as a supportive mechanism rather than a replacement for managerial judgement.

From a theoretical perspective, the study contributes to the intersection between risk perception theory, behavioural decision-making, and AI-supported project management. The findings reinforce existing critiques of purely rational approaches to risk management by demonstrating that risk perception remains strongly shaped by experience, communication, organisational structures, and contextual interpretation. Although AI tools may improve access to information and analytical capabilities, the interpretation of uncertainty continues to depend largely on

human actors. In this sense, the findings extend behavioural and interpretive perspectives on risk management into the context of AI-supported decision-making.

The findings also contribute to the literature on technology adoption within organisations. Existing research often presents AI adoption as closely connected to perceived usefulness, efficiency, and technological capability. While the interviews conducted in this study support these arguments to some extent, they also show that adoption is heavily influenced by organisational maturity, governance structures, confidentiality concerns, and trust in AI-generated outputs. This suggests that the practical integration of AI within project environments is not solely a technological issue, but also an organisational and social process shaped by institutional context and managerial attitudes.

Another important theoretical implication concerns the relationship between AI and contextual complexity. The findings indicate that AI appears most useful in structured and measurable environments where information can be processed systematically. In contrast, situations involving stakeholder dynamics, political uncertainty, communication challenges, or rapidly changing project conditions continue to require contextual interpretation and adaptive judgement from project managers. This supports the broader argument emerging throughout the thesis that AI currently complements rather than replaces human-centred decision-making processes in complex project environments.

From a practical perspective, the findings suggest that organisations should approach AI-supported risk management strategically and selectively. Rather than viewing AI as a fully autonomous decision-making system, organisations may benefit more from positioning AI as a support tool that enhances analytical capacity, improves efficiency, and assists with information processing. The findings indicate that AI can provide significant value in tasks such as identifying patterns, processing large volumes of information, supporting reporting processes, and generating initial insights. However, human oversight remains essential for interpreting outputs and evaluating contextual relevance.

The findings also highlight the importance of maintaining critical thinking and reflective judgement when using AI-supported systems. Several respondents expressed concerns regarding over-reliance on AI and the possibility that project managers may gradually place excessive trust in automated outputs. Organisations implementing AI-supported tools should therefore ensure that employees remain capable of critically evaluating AI-generated information rather than accepting it uncritically. This may require not only technological implementation, but also training, governance structures, and clear organisational guidelines regarding the responsible use of AI in decision-making processes.

In addition, the findings suggest that communication and organisational culture remain central components of effective project risk management, regardless of technological development. Since many risks emerge through stakeholder interaction, coordination challenges, and contextual uncertainty, organisations should avoid viewing AI as a substitute for communication, collaboration, or managerial experience. Instead, AI-supported systems

appear most effective when integrated into broader organisational processes that still prioritise human interaction and contextual understanding.

Overall, the findings of this study suggest that AI-supported project risk management should be understood as a hybrid process in which technological tools and human judgement operate together. While AI provides valuable analytical support, project managers remain responsible for interpreting uncertainty, understanding context, and making final decisions. The study therefore contributes to a more balanced understanding of AI within project environments by highlighting both its practical value and its current limitations in managing complex and uncertain international projects.

5.6 Integrated Conceptual Framework

The integrated conceptual framework (**Figure 5**) illustrates the central findings of this thesis and demonstrates how AI-supported tools, human risk perception, and organisational context interact within international project environments. While the initial conceptual framework focused on identifying the research gap between AI in project management, managerial perception, and international project risk management, the integrated framework reflects how these relationships were further developed through the empirical findings and subsequent analysis.

At the centre of the framework is **risk-related decision-making**, which emerged as the core process connecting managerial judgement, AI-supported systems, and organisational context. The findings indicate that project risk management is not shaped by technological systems alone, but through the continuous interaction between human interpretation and AI-supported analytical processes.

The framework positions **AI-supported tools** as a supportive and complementary component within project risk management. Across the interviews, respondents described using AI primarily for predictive analytics, data processing, reporting support, pattern recognition, and information generation. These tools were perceived as valuable in improving efficiency and supporting structured analytical tasks, particularly in data-driven environments. However, the findings also showed that AI-generated outputs require validation, contextual interpretation, and critical evaluation before they can be integrated into practical decision-making processes.

For this reason, the framework highlights **human risk perception and interpretation** as a central element within international project risk management. The findings consistently demonstrated that project managers rely heavily on contextual understanding, experience-based judgement, stakeholder awareness, and communication processes when interpreting uncertainty and making decisions. Particularly in complex international projects, respondents emphasised that many risks emerge through relational dynamics, organisational interaction, and changing external conditions that cannot easily be reduced to purely technical analysis.

The framework further demonstrates the importance of **organisational and international context** as a shaping and moderating influence on both AI adoption and managerial decision-making. Governance structures, communication practices, organisational maturity, cultural differences, institutional variation, and cross-border complexity all influence how risks are perceived and how AI-supported systems are utilised in practice. The findings showed that these contextual conditions affect not only the management of project risk itself, but also the level of trust placed in AI-generated outputs and the willingness of organisations to integrate AI-supported systems into existing processes.

Another important component reflected in the framework is the role of **trust and adoption factors**. The analysis demonstrated that AI adoption is shaped not only by technological capability, but also by perceived usefulness, transparency, reliability, data quality, and organisational confidence in AI-supported outputs. Respondents generally expressed conditional trust in AI systems, particularly in situations involving ambiguity, stakeholder-sensitive decision-making, or rapidly changing project environments.

Overall, the integrated conceptual framework demonstrates that project risk management in international environments should be understood as a hybrid and interactive process in which AI-supported tools and human judgement operate together rather than independently. The framework reflects the central conclusion of this thesis: while AI can significantly support analytical and administrative aspects of project risk management, the interpretation of uncertainty and the final decision-making process remain fundamentally dependent on human judgement, contextual understanding, and organisational interaction.

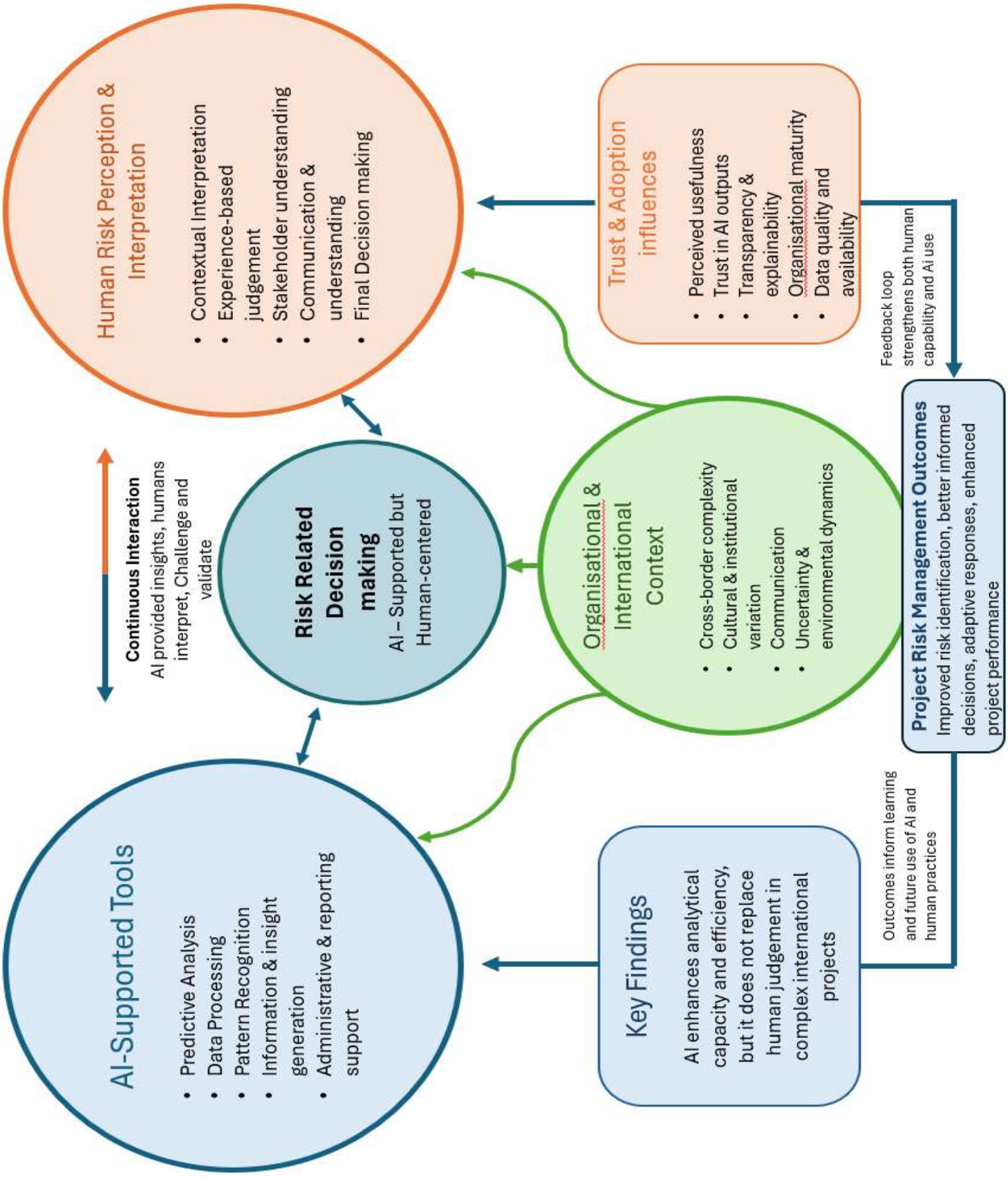

Figure 5 "Integrated conceptualisation framework"

6 Conclusion

This thesis examined how project managers in international organisations perceive and utilise AI-supported tools in risk-related decision-making processes within international projects. The study focused on the relationship between risk perception, organisational context, and the practical use of AI-supported systems in complex project environments. Through qualitative interviews with project professionals from different organisational and international settings, the research explored how risk is interpreted and managed in practice, as well as how AI is integrated into these processes.

The findings demonstrate that **risk perception in international projects is highly contextual and strongly dependent on human interpretation**. Although formal risk management frameworks and structured procedures remain important, project managers consistently described risk as something shaped by communication, stakeholder relationships, organisational structures, and changing environmental conditions. Risk was therefore perceived not only as a measurable technical issue, but also as a dynamic organisational and relational process influenced by uncertainty and contextual complexity.

The study also found that **organisational and international context significantly shape risk management practices**. Structured organisations with formal governance systems generally applied more systematic and standardised approaches to risk management, while more decentralised environments relied more heavily on individual judgement and informal processes. International projects introduced additional layers of complexity related to cultural differences, institutional variation, political uncertainty, and communication across geographically distributed teams. These factors increased the importance of flexibility, contextual understanding, and adaptive decision-making within project environments.

In relation to AI-supported tools, the findings indicate that **AI currently functions primarily as a support mechanism rather than an autonomous decision-making system**. Respondents described using AI mainly for administrative support, information processing, analytical assistance, and idea generation. In more structured and data-driven environments, AI-supported systems also contributed to pattern recognition, anomaly detection, and reporting visibility. However, across all interviews, project managers consistently emphasised the need to validate and interpret AI-generated outputs before incorporating them into decision-making processes.

A central conclusion of this thesis is therefore that **human judgement remains fundamental to project risk management**, particularly in complex international environments characterised by uncertainty, stakeholder interaction, and contextual variation. While AI can improve efficiency and support analytical processes, it does not replace the need for managerial interpretation, contextual awareness, and experience-based judgement. Instead, the findings suggest that AI currently operates most effectively as a complementary tool that augments rather than replaces human decision-making.

From a theoretical perspective, the study contributes to existing research by connecting risk perception theory, behavioural decision-making, organisational context, and AI-supported project management within a single analytical framework. The findings reinforce critiques of purely rational approaches to risk management and demonstrate that the practical use of AI in project environments remains strongly shaped by organisational structures, communication processes, trust, and contextual complexity.

From a practical perspective, the findings suggest that organisations should adopt AI-supported tools strategically while maintaining strong human oversight within project risk management processes. AI appears particularly useful in structured and data-driven tasks, whereas communication, stakeholder management, and contextual interpretation remain areas where human capabilities continue to play a decisive role.

Overall, this thesis shows that **AI-supported risk management in international projects remains fundamentally human-centred**. Although AI technologies are likely to become increasingly integrated into project environments, the perception, interpretation, and management of risk continue to depend primarily on human judgement, organisational interaction, and contextual understanding.

6.1 Limitations

While this study provides insights into how project managers perceive and utilise AI-supported tools in risk-related decision-making processes within international projects, several limitations should be acknowledged when interpreting the findings. These limitations relate primarily to the methodological approach, the scope of the sample, and the evolving nature of AI adoption within project management environments.

First, the study adopted a qualitative and interpretive research design based on semi-structured interviews. This approach was appropriate for exploring managerial perceptions, contextual interpretation, and organisational experiences in depth. However, qualitative research prioritises detailed understanding over statistical generalisation. As a result, the findings should be understood as context-dependent insights into project risk management practices rather than universally generalisable conclusions applicable to all organisations or industries.

A second limitation relates to the sample size and composition of the study. The research was based on interviews with ten project professionals working in international project environments across different organisational contexts. While the respondents provided substantial practical insight and represented diverse experiences, the sample remains relatively limited in size. In addition, many respondents operated within international, consultancy-oriented, or project-intensive organisational environments, which may influence how risk management practices and AI-supported tools are perceived. Organisations operating in significantly different industries or less internationally oriented environments may therefore experience different challenges and approaches.

Another important limitation concerns the reliance on self-reported perceptions and experiences. The findings are based on how respondents described their own practices, decision-making processes, and interactions with AI-supported systems. As with most interview-based research, responses may be influenced by subjective interpretation, retrospective reflection, or individual bias. The study therefore reflects managerial perceptions of AI-supported risk management rather than direct observation of organisational behaviour in practice.

The rapidly evolving nature of artificial intelligence also represents an important limitation. AI-supported technologies are developing quickly, and organisational adoption remains uneven across industries and project environments. The findings of this study therefore reflect a specific stage in the current development and practical integration of AI within project management processes. As AI technologies become more advanced and organisations develop more mature implementation strategies, managerial attitudes, trust levels, and practical use cases may change significantly over time.

In addition, the study adopted a cross-sectional rather than longitudinal perspective. The interviews were conducted within a limited time period and therefore capture perceptions and practices at a specific moment rather than examining how AI adoption and risk management practices evolve over time. Future changes in organisational processes, technological maturity, and international project environments may influence how AI-supported systems are integrated into decision-making processes in the future.

Despite these limitations, the study contributes to the growing body of research examining the relationship between AI-supported technologies, managerial judgement, and project risk management in international environments. The findings provide insight into how project managers currently interpret and utilise AI-supported systems within complex organisational settings and highlight the continued importance of contextual understanding and human judgement in risk-related decision-making processes.

Future research could expand upon this study in several ways. Quantitative research could be used to test the broader generalisability of the findings across larger samples and industries. Longitudinal studies could examine how AI adoption and managerial trust evolve over time as organisations gain greater experience with AI-supported systems. Comparative studies between industries or regions could also provide deeper insight into how organisational culture, governance structures, and institutional environments influence AI-supported risk management practices. Finally, future research may further explore the evolving relationship between human judgement and increasingly advanced AI-supported decision-making systems within complex project environments.

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8 Appendices

Appendix 1 – Initial Interview guide

Original Semi-Structured Interview Questions

Initial interview guide used for the primary data collection

1. 1. Background and Context

1. Can you describe your role and your experience with project management, especially in international projects?

2. 2. Understanding and Managing Risk

2. How do you understand and deal with risk in your projects?
3. Can you describe how risk is typically identified and managed in your organisation?
4. Can you share an example of a situation where risk or uncertainty played an important role?

3. 3. International and Organisational Influences

5. How do international aspects, such as working across countries or cultures, influence how you approach risk management?
6. How do your company's structure and decision-making processes influence how risks are identified and managed in your projects?

4. 4. Use of AI and Digital Tools

7. Can you describe if and how you use digital or AI-based tools in your work, particularly for risk management?
8. What impact do these tools have on how you identify or assess risks?

5. 5. Perceptions and Trust in AI

9. How do you feel about using AI or data-driven tools when making decisions about risk?
10. What influences whether you trust or rely on these tools?

6. 6. Human–AI Interaction and Future Outlook

11. How do you combine your own experience with insights from AI tools when making decisions?
12. How do you see the role of AI in project risk management developing in the future?

Figure 6 – Initial interview guide

The original semi-structured interview guide was developed primarily through the **a priori conceptual framework** established after the literature review. This framework connected three main areas: AI in project management, managerial perception and decision-making, and risk management in international projects. Based on these theoretical areas, the first set of interview questions was designed to explore the respondent's project management background, their understanding of risk, the influence of international and organisational contexts, and their use and perception of AI-supported tools. In this sense, the initial interview guide was theory-led and ensured that the primary data collection was directly connected to the research question and the key concepts identified in the literature review.

Appendix 2 – Final Interview guide

Final Interview Guide

Questions Used for the Final Interview

1. 1. Background and Project Context

1. Can you briefly describe your role and your experience with project management, especially in international or cross-organisational projects?
2. What types of projects do you usually work on, and what makes them complex or uncertain?

2. 2. Risk Perception and Contextual Complexity

3. How do you personally understand risk in your projects?
4. In your experience, what kinds of risks are most difficult to identify or manage?
5. How do factors such as country context, political conditions, culture, regulations, or stakeholder behaviour influence the way risks appear in your projects?

3. 3. Risk Management as a Continuous and Proactive Process

6. At what stage of a project are risks usually identified, and how are they followed up during implementation?
7. Can you describe a situation where identifying a risk early helped avoid a larger problem later?
8. How do you deal with risks that change, disappear, or emerge unexpectedly during the project?

4. 4. Formal and Informal Risk Management Practices

9. What formal tools or procedures does your organisation use to identify, assess, or monitor risks?
10. Besides formal tools, how are risks identified informally, for example through team discussions, intuition, experience, or everyday communication?
11. How do formal procedures and informal judgement work together in your organisation's risk management practices?

5. 5. Communication, Culture, and Stakeholder Relations

12. How does communication between teams, clients, beneficiaries, or partners influence risk management in your projects?
13. Can you describe a situation where communication, cultural expectations, or stakeholder relationships created or reduced risk?
14. How important is openness or the willingness to raise concerns early in managing project risks?

6. 6. Use of AI and Digital Tools

15. What digital or AI-supported tools do you use in your project work, if any?
16. What do you mainly use these tools for, for example drafting, research, reporting, monitoring, forecasting, or identifying patterns?
17. Have AI or digital tools changed how you identify, assess, or think about risks? If yes, how?

7. 7. Trust, Limitations, and Human Judgement

18. What makes you trust or distrust AI-generated outputs in project-related work?
19. How do you check or validate outputs from AI or data-driven tools before using them?
20. In what types of project situations do you think AI is useful, and where do you think it is limited?
21. How do you combine AI-generated insights with your own experience, judgement, or knowledge of the project context?

8. 8. Future Outlook

22. How do you think the role of AI in project risk management will develop in the future?
23. What would need to change in organisations for AI to become more useful or trustworthy in risk management?

Figure 7 – Final interview guide

The second interview guide was developed through the **abductive logic** of the study. As the interviews were conducted and coded, new empirical insights emerged that were not fully captured in the original guide. Themes such as contextual complexity, informal risk identification, communication and culture, organisational maturity, trust in AI, and the limits of AI in complex decision-making became increasingly important. These findings led to a return to the literature review and conceptual framework, after which the interview questions were refined to better explore these emerging patterns. The final interview guide therefore reflects an iterative movement between theory and empirical data, where the original framework guided the research, but the coded interviews helped reshape and deepen the later questions.

Appendix 3 - All interview transcripts

The full interview transcripts are attached as a separate appendix file. These transcripts provide the complete empirical material used in the analysis and allow the reader to review the original interview data in full. The transcripts form the basis for the coding process and support the transparency of the qualitative research design.

Appendix 4 - All interviews coded

The coded interview material is attached as a separate appendix file. This document shows how the interview data was coded and organised during the analysis process. It provides additional transparency by allowing the reader to trace how selected statements were connected to codes, categories, and the final themes used in the analysis chapter.

Appendix 5 - Ethical Considerations and Participant Consent

All interview participants consented to taking part in the research and to the use of their professional perspectives within the thesis. The interviews were conducted for academic purposes and focused on participants' professional experiences with project management, risk management, international project environments, and AI-supported tools.

To improve clarity and analytical traceability, participants are referred to throughout the analysis using interview identifiers from Int1 to Int10. These identifiers allow the reader to connect statements and quotations in the analysis to the interviewee overview table without interrupting the flow of the chapter. The use of identifiers also supports transparency by making it possible to trace how specific empirical insights contributed to the development of the final themes.

The interview data was handled carefully and used only for the purposes of this research. The full transcripts and coded interview material are attached as separate appendix files to support transparency and allow the reader to review the empirical basis of the analysis.