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Human and Artificial Intelligence Collaboration to Enhance Agile Project Management Performance

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ABSTRACT:

The use of Artificial Intelligence (AI) in Agile project management is transforming sprint planning, team communication, and project delivery. But Agile project management heavily depends on the human judgment, leadership, creativity, ethics, and teamwork. Therefore, the focus of this thesis is to explore how human and Artificial Intelligence collaboration enhances Agile project management performance. Agile project management practitioners from various industries and roles, such as Product Owners, Project Managers, Scrum Masters, and Developers, participated in the survey. Data was analysed using descriptive statistics, reliability analysis, cross tabulation, and Pearson correlation. The study concentrates on five areas: current use of AI in Agile project management activities, the ongoing role of humans, the impact of Human–AI collaboration on the Agile project management performance, challenges of AI implementation, and strategies for overcoming challenges to improve Human–AI collaboration. The results reveal that AI tools have been integrated at various stages of the Agile lifecycle, particularly in team communication, sprint planning, backlog management, reporting, and for support with regularly performed tasks. The most popular tools were generative AI assistants and AI project management platforms. However, respondents strongly agreed that human expertise remains irreplaceable, especially in ethical decision-making, creative problem-solving, leadership, stakeholder negotiation, and contextual judgment. Human-AI collaboration was seen as enhancing Agile performance, especially overall project performance, communication transparency and the quality of decisions. Meanwhile, the biggest hurdles were the inaccuracy or misinformation of AI-generated content, data privacy and security issues, integration complexity, and trust in AI-generated content. The study concludes that AI enhances Agile project performance when it is used to assist, not replace, human efforts. Clear human oversight, training, validation processes, trust, and data governance are the most effective sources of performance improvements. The thesis goes on to suggest a conceptual framework of four layers: AI support, human role, governance and trust, and Agile performance outcomes, which is built on these findings.

KEYWORDS: human and AI collaboration, artificial intelligence, agile project management, project management performance.

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Abbreviations

AI – Artificial Intelligence

APM – Agile Project Management

API – Application Programming Interface

CI/CD – Continuous Integration / Continuous Deployment

EU – European Union

GDPR – General Data Protection Regulation

GenAI – Generative AI

HITL – Human-in-the-Loop

IT – Information Technology

LLM – Large Language Model

ML – Machine Learning

NLG – Natural Language Generation

NLP – Natural Language Processing

SAFe – Scaled Agile Framework

SD – Standard Deviation

TAM – Technology Acceptance Model

XAI – Explainable Artificial Intelligence

1 Introduction

This section introduces the background of this study, key concepts, problem statements, research questions, research objectives, an overview of the methodology, and the structure of this paper.

1.1 Background of the Study

The Agile manifesto was introduced in 2001 (Beck et al., 2001). In the current world, Agile project management is widely used because it is user-centric, flexible to changes, and it supports continuous delivery and iterative development processes (Dong et al., 2024). At the same time, project environments are becoming more complex. Globalization, remote collaboration, and technological developments have affected recent projects. Consequently, different tools, large amounts of data, and faster decision-making present a problem to the teams. These are making it difficult to plan sprints, estimate, and timeline, and identify risks (Hughes et al., 2025).

Project work is now supported using Artificial Intelligence (AI). AI can analyze vast amounts of data and identify trends that a person can ignore. To illustrate, AI can assist in sprint planning and work backlog by assisting teams to estimate and predict results (Lumbanraja et al., 2024). AI is also applicable to the process of decision-making as it can be used to connect data obtained in such tools as Jira and Trello and subsequently display dashboards and alerts in real time (Almalki, 2025).

Moreover, other studies indicate that AI can also forecast the status of Agile projects based on agility features and can justify the forecast, which builds trust and transparency (ForouzeshNejad et al., 2025).

However, Agile project management is still human-dependent. It depends on leadership, communication, negotiation, and teamwork. This is why it is not sufficient to simply introduce AI to an Agile project. Rather, Agile must apply AI to increase productivity and retain human beings and their values to act (Hoda et al., 2023; Hussain et al., 2021). The latest advancements in generative AI and cognitive agents provide a possibility of better coordination in large-scale Agile but require human control to eliminate ethical concerns and biases (Cinkusz et al., 2024; Dawarka et al., 2025).

Here, AI applications are employed to provide information-based solutions and robots to perform repetitive tasks, and the human mind is involved in contextual judgment, leadership, and human collaboration (Hughes et al., 2025).

Moreover, AI will automate a significant proportion of the routine project processes and improve efficiency by a significant margin in the decade to come (Alevizos et al., 2024). For this reason, a model is necessary which is to combine AI automation with human beings in the Agile project framework.

On this basis, this thesis focuses on the enhancement of collaboration, as opposed to replacement, exploring the contribution of hybrid strategies to the excellent project outcomes.

1.2 Key concepts

1.2.1 Human in Agile project management

In this thesis, 'human' refers to practitioners who apply experience-based judgment, leadership, and interpersonal skills within Agile teams. The primary positions in Agile Project Management include the Product Owner, Scrum Master, and agile teams. Ethical decisions, trade-offs among the stakeholders, and managing conflict require human expertise. (Dawarka et al., 2025).

1.2.2 AI tools in Agile project management

The AI tools in this thesis are systems available that rely on machine learning, predictive analytics, natural language processing, or automation to assist Agile work. Such tools would be AI agents or other generative AI systems. As an illustration, project status predictive models, artificial intelligence to support risk and resource allocation decisions, and artificial intelligence to aid retrospectives (Almalki, 2025).

1.2.3 Agile project performance

Agile project performance in this thesis refers to the effectiveness of an Agile project in delivering good results. It comprises predictability of sprint, reliability of delivery, handling risks, quality of decisions, and effectiveness of the team. Studies indicate that AI would enhance prediction and decision support in Agile projects, and this is directly associated with the performance results (Almalki, 2025; Koudriachov et al., 2025).

1.3 Problem Statement & Research Gap

1.3.1 Problem statement

Agile projects are embracing the use of AI tools by many organizations. Nevertheless, they remain uncertain about things that can improve performance in practice. It may result in inappropriate risk management and ineffective resource distribution (Almalki, 2025). Simultaneously, AI tools have the potential to give rise to new issues, including black-box predictions and low trust (ForouzeshNejad et al., 2025). Moreover, intelligent AI agents can fail to comprehend unclear requirements and can cause bias. That is, it still requires human supervision (Cinkusz et al., 2024). In this regard, experience and personal judgment are relied upon in the decisions of projects. Therefore, the nature of how to use AI is not the main issue. The actual issue is the necessity to integrate AI assistance with human knowledge in such a manner that maximizes the results of Agile.

1.3.2 Research gap

Current research has an understanding of AI technical capabilities in Agile project management. There are some gaps that are identified and directly addressed by this thesis.

Firstly, AI and human inputs in an agile environment are researched separately. The majority of research is dedicated to the AI technologies' capabilities, such as sprint forecasting, backlog refinement, and risk prediction (Almalki, 2025; ForouzeshNejad et al., 2025). Other articles focus on such human factors as leadership and teamwork independently (Diebold, 2025; Hussain et al., 2021). There is a very small number of studies examining both humans and AI.

Second, there are some validated human and AI collaboration frameworks. Other scholars have come up with concepts, such as the concept of augmented agile and AI-based project management architecture (Dam et al., 2019; Hoda et al., 2023). None of these has been put through to real practitioners. This was also observed by Hashfi and Raharjo (2023), who believed that practical research was required to relate AI implementation with Agile frameworks.

Third, there is a lack of empirical evidence in the real world. The majority of research is founded on the lab or pilot programs, rather than the live Agile teams (Almalki, 2025; Taboada et al., 2023). It is not well known how AI tools are actually implemented by the Agile practitioners in their routines, in their day-to-day tasks like sprint planning, standups, or retrospectives.

Fourth, human and AI challenges in Agile are not well studied. There are many problems, such as AI hallucination, black-box AI predictions, lack of trust, and team resistance are listed in the literature but not extensively discussed in the context of Agile (Cinkusz et al., 2024; ForouzeshNejad et al., 2025).

1.4 Research Questions and Objectives

The main research question of this study is:
How does human and Artificial Intelligence collaboration improve project performance in Agile project management?

To answer this question, the study has the following objectives:

1. Identify Agile activities where AI tools are presently applied.
2. Identify the role of humans in decision-making, managing AI, leadership, problem-solving, and team collaboration.
3. Find the impact of human–AI collaboration on Agile project management performance.
4. Identify challenges related to AI implementation in Agile Project Management and the strategies to overcome these challenges.
5. Develop a conceptual framework for effective human–AI collaboration in an agile project management framework.

1.5 Scope of the Study

This thesis is primarily about Agile project environments, particularly software, technology, and industrial projects. It looks at the integration of humans with AI tools in Agile work. The paper is aware of the Agile activities and ceremonies such as Backlog Refinement, Sprint Planning, Daily Scrum, Sprint Review, and Sprint Retrospective. These key elements include planning, analysis, prediction, coordination, monitoring, report generation, feedback, and improvement. This research does not focus on the creation and implementation of a new AI system in an organization. Rather, it explores how much AI is being used now, its impact perceived at present, and the potential for collaboration between AI and humans using survey data and literature. The focus is on the Agile project setting and is not comprehensive of the traditional project management setting.

1.6 Overview of Methodology

This research follows a quantitative research approach, which is used to answer the research questions and research objectives. The primary data will be obtained by surveying a structured sample of Agile practitioners, such as Scrum Masters, Product Owners, and Project Managers and agile practitioners. The survey will collect quantitative data regarding the use of AI, human role, challenges, solutions to the challenges, and the impact on performance perceived.

1.7 Structure of this Thesis

This thesis contains six chapters.
Chapter 1: introduces the topic, background of the study, defines key concepts, presents the problem statement, research gap, research question, overview of methodology, and the scope of the study.
Chapter 2: Reviews literature on Agile project management, overview of the most popular agile framework, Scrum, AI in Agile, human role in Agile project management, and human–AI collaboration in APM.
Chapter 3: Describes the methodology, research approach, research design, data collection process, data analysis, sampling, validity and reliability, and methodological limitations.
Chapter 4: Presents the results and analytical findings.
Chapter 5: Discusses the results.
Chapter 6: Concludes the thesis and provides limitations, recommendations, and future research directions.

2 Literature Review

This chapter offers a thorough literature review of the selected literature on the topic of the thesis. It starts with a theoretical framework. After that, the summary of Agile Project Management, and then proceeds to analyse how humans are relevant in Agile project management. It then examines how Artificial Intelligence can be incorporated into project management, including how it can be used in Agile. Thereafter, the review explores the interaction between humans and AI, with the emphasis on the new frameworks and issues. Lastly, it makes inferences on the findings to highlight the major research gaps that will be filled by this research.

2.1 Theoretical Framework

The frameworks mentioned below have been chosen for their ability to cover the technological, social, cognitive, and collaborative aspects of incorporating AI tools into human-centred agile project management.

2.1.1 Knowledge Management Theory

The theory of Knowledge Management focuses on the process of knowledge generation, sharing, and utilization in organizations (Nonaka & Takeuchi, 1995). It is divided into two parts: explicit knowledge (documents and stored) and tacit knowledge (experience, judgment, and interaction).

AI tools are effective in explicit knowledge, such as generating reports, analyzing sprint data, and forecasting velocity. AI tools excel in explicit knowledge, including report generation, sprint data analysis, and velocity prediction. But, there is also tacit knowledge, which is created in the process of working with a team, trust, and common experience, which can't be replaced by AI. The tacit knowledge possessed by a team is the most valuable knowledge, as argued by Grant (1996), because it is difficult to automate such knowledge.

2.1.2 Socio-technical Systems Theory

The Socio-technical Systems Theory is concerned with the interaction between social and technical aspects of an organization (Trist & Bamforth, 1951). In agile project management, the technical aspect is the components of AI tools, while the social aspect is the human team. Both must be a fit and a relationship between both sides. The team is more effective when they are in perfect synchronization with AI tools. However, this theory can help explain how AI tools can be integrated into agile teams without causing disruption to their working environment.

2.1.3 Technology Acceptance Model

The Technology Acceptance Model describes the factors that affect to make a decision to implement new technology (Davis, 1989). It's about two essential things. One is use, and another is usability. If AI tools help and are easier to use, then team members will use them. Otherwise, they will refuse to use AI tools. This model has been proven to clarify agile practitioners when AI tools are adopted into their practices. The model offers insights into agile practitioners' responses to the integration of AI tools into their work processes.

2.2 Overview of Project Management

A project is a unique, temporary effort undertaken to produce a product, service, or result with specific goals, time requirements, and organizational resources (Koudriachov et al. 2025). Project management is the systematic use of knowledge, tools, and techniques to achieve those temporary undertakings and meet the intended objectives without interference. It is a discipline that spans the end-to-end product or service delivery lifecycle from envisioning the initial product or service to its execution, delivery to the customer, and support after the delivery (Breyter, 2022).

Traditional project management approaches are commonly linked to the 'Waterfall' model, which has been used for years and is characterized by a sequential process of project phases, including initiation, planning, execution, monitoring, and closing (Cobb, 2023). Project success was primarily measured in these traditional, plan-driven environments by project time, budget, and scope or quality (Breyter, 2022). These constraints were usually considered fixed at the initial point of the project, which made the process of changing the scope of the project, even if the scope was to change, very challenging and stringent, as the traditional approach was very rigid and focused on predictability and control (Cobb, 2023).

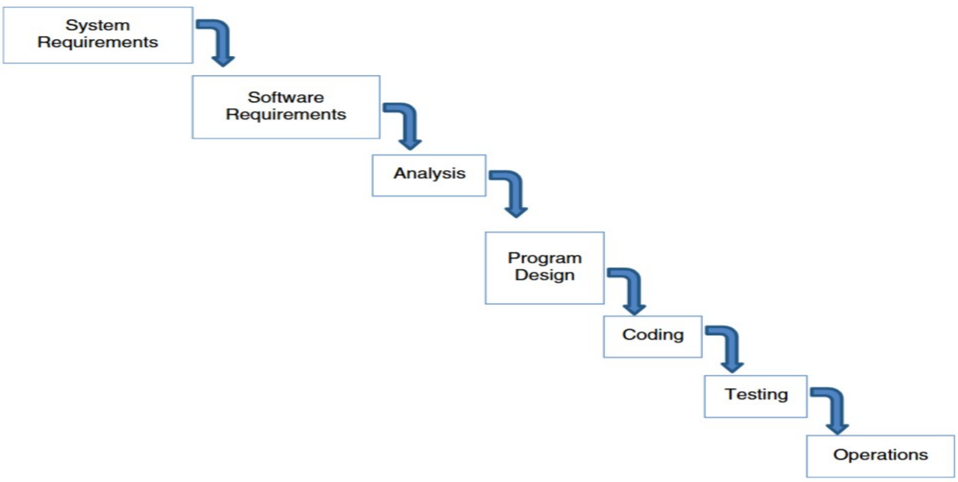

Figure 1. Traditional or Waterfall Project Management (Cobb, 2023).

2.3 Overview of Agile project management

Agile Project Management (APM) focuses on flexibility, iterative development, and collaboration with customers. The core values are contained in the Agile Manifesto, which places more emphasis on people and communication than on processes and tools, working software than on detailed documentation, customer collaboration than on contract negotiation, and responding to change than a rigid plan (Beck et al., 2001). The Agile framework has evolved to incorporate different frameworks, including Scrum, Kanban, and Lean, that support adaptive planning and continuous improvement of dynamic project environments (Layton et al., 2025).

Practically, APM allows teams to address the complexity with short cycles called sprints during which deliverables are evaluated and revised in response to the feedback. This method has become popular in the software development industry among others because it is fast to deliver and also to engage the stakeholders (Koudriachov et al., 2025). Nevertheless, there are still issues, such as how to scale Agile in bigger companies and how to keep teams falling together in the distributed environment (Saklamaeva & Pavlič, 2023). Recent systematic reviews further note that while Agile promotes flexibility, its effectiveness depends heavily on human factors rather than processes alone (Koudriachov et al., 2025).

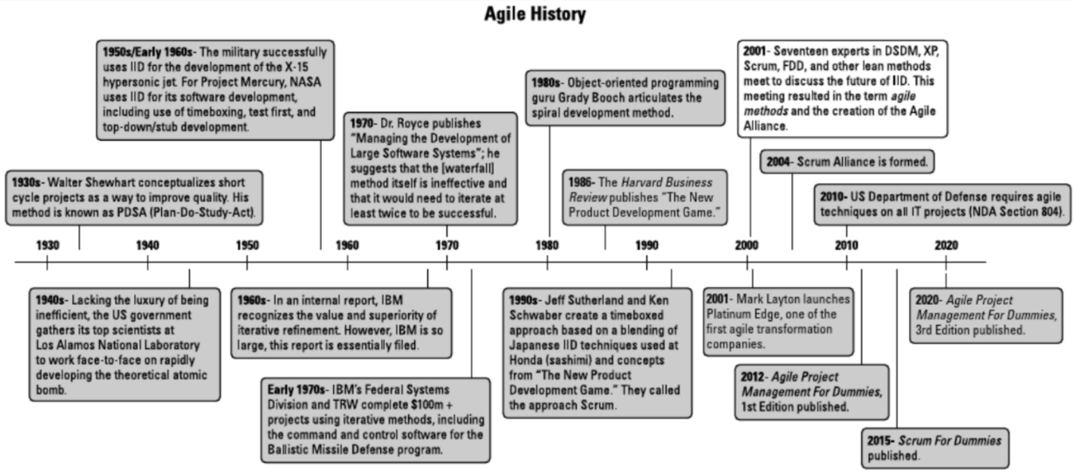

Figure 2. Timeline of Agile Project Management (Layton et al., 2025).

2.3.1 Four Values of the Agile Manifesto

Agile Project Management was introduced in 2001 as a critical response to the limitations and rigid structures of traditional waterfall or plan-driven methodologies. prioritizing adaptability, collaboration, and human-centric approaches (Dong et al., 2024). As a

result, they published the Agile Manifesto, which established four core values that advocate for a fundamental shift in development philosophy. These values are:
"1. Individuals and interactions over processes and tools; 2. Working software over comprehensive documentation; 3. Customer collaboration over contract negotiation; 4. Responding to change over following a plan" (Beck et al., 2001).

The values-driven approach is intended to optimize the process of complex and dynamic projects, leading to a collaborative approach and the focus on the customer's requirements in the delivery of the project (Saklamaeva & Pavlič, 2023).

2.3.2 Twelve Principles of Agile

There are 12 principles to support the Agile Manifesto, which are designed to help teams deliver value in uncertain and changing environments (Beck et al., 2001). These principles can be grouped into four categories.

1. Customer focus and delivery: The key objective is to satisfy the customer by delivering working software early and continuously. Teams need to be delivering results regularly, preferably on a short timeframe, and at all times should embrace the changing nature of requirements, even late in the project.

2. People and collaboration: Agile sees that the best outcomes are achieved by motivated people working close to each other. Business stakeholders and developers must work with each other every day during the project. In a team, face-to-face communication is the best method for sharing information.

3. Quality and simplicity: Work groups need to be constantly and continually mindful of technical quality and good design. Keep it simple, and only do what is needed, and do not do more. Teams that are allowed to self-organise and are trusted to make decisions are the best solutions.

4. Continuous improvement: Agile encourages working sustainably, for the long term. Teams periodically review their performance and adjust accordingly so that they are more effective. This fosters a learning and adapting environment.

These twelve principles help Agile teams to be flexible, open, to create real value, and to continuously improve how they work (Beck et al., 2001).

2.4 Traditional Project Management vs. Agile Project Management

Traditional project management is linear, has a defined project plan and phases. Agile project management, on the other hand, is flexible and iterative and offers a way to make continuous changes, collaborate with others, and continuously deliver value. Hence, Agile is more appropriate in a dynamic environment with requirements changing often (Koudriachov et al., 2025).

Table 1. Project Management vs. Agile Project Management (Koudriachov et al., 2025).

Aspect	**Traditional Project Management**	**Agile Project Management**
Nature	Linear, structured, sequential	Iterative, flexible, adaptive
Planning	Fixed plan at start	Continuous adaptation
Control	Manager driven	Team-driven
Delivery	One final delivery	Incremental delivery (sprints)
Focus	Scope, cost, time	Value, collaboration, customer feedback

2.5 Overview of Scrum

According to Breyter (2022), Scrum is defined as a lightweight framework developed to help teams and organizations generate value through adaptive solutions for complex problems. It is currently the most popular agile methodology, used by approximately 58% of organizations to manage software development and other complex projects (Breyter, 2022). Scrum also incorporates Lean thinking to focus on waste reduction (Cinkusz et al., 2024).

The framework operates through three core pillars defined by Breyter (2022):

1. Transparency, requiring that the emergent process and work be visible.
2. Inspection, involving frequent checks of artifacts and progress.
3. adaptation, which necessitates immediate adjustments when deviations are detected.

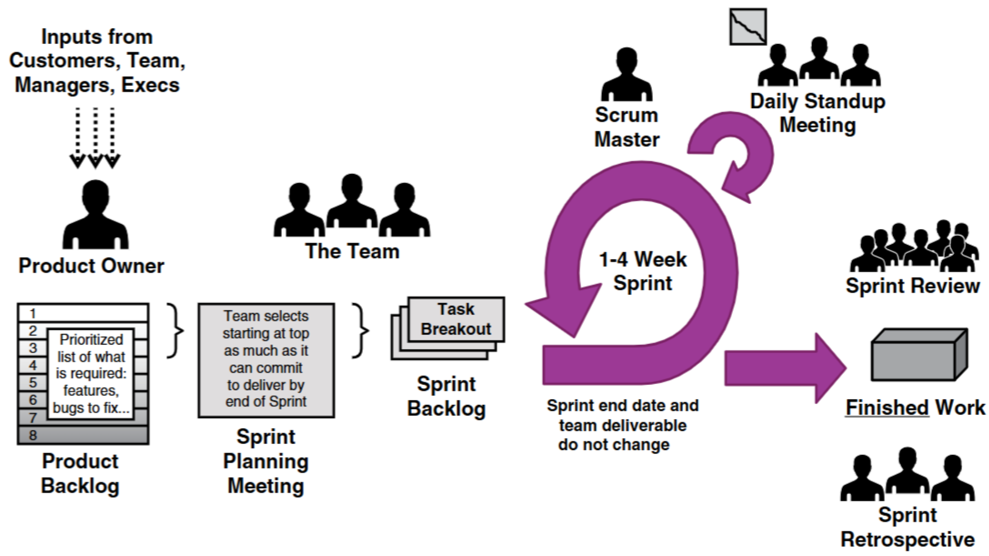

Figure 3. Scrum Framework (Cobb, 2023).

2.5.1 Scrum Roles

The Scrum Team is a small, cross-functional, and self-organizing unit consisting of three specific roles (Cobb, 2023) :

1. Product Owner: Accountable for maximizing the value of the product and managing the Product Backlog.
2. Scrum Master: A servant-leader responsible for ensuring Scrum is understood and enacted by coaching the team and removing impediments.
3. Developers: Professionals committed to creating any aspect of a usable increment each Sprint.

2.5.2 Scrum Events

Scrum execution occurs in Sprints, which are fixed length timeboxes of one month or less. Each Sprint includes the following ceremonies (Cobb, 2023):

1. Sprint Planning: A meeting where the team defines a Sprint Goal and selects items for the current cycle.
2. Daily Scrum: A 15-minute daily event for Developers to inspect progress toward the Sprint Goal.
3. Sprint Review: An event held at the end of the Sprint to inspect the outcome and determine future adaptations.
4. Sprint Retrospective: The final event where the team inspects itself and plans improvements for the next cycle.

2.5.3 Scrum Artifacts

Scrum artifacts are designed to provide transparency and include (Cobb, 2023):

1. Product Backlog: An evolving, ordered list of everything needed in the product.
2. Sprint Backlog: The specific items selected for the Sprint and a plan for delivering the Increment.
3. Increment: The sum of all completed Product Backlog items that meet the team’s Definition of Done.

2.6 Essential Human Roles in Agile Project Management

The human role is very crucial in Agile projects. Since routine Agile activities are automated by AI technologies (Alliata et al., 2025). But the human role is essential for high-value mental and social areas such as decision-making, leadership, and teamwork. The Agile teams know how to apply judgment in their work based on experience, interpersonal skills, and knowledge of the domain, which is needed in Scrum Masters and Product Owners roles (Gandomani et al., 2020).

2.6.1 Product Sense and Vision

The product owner's role is not just to create a product, but the product owner has long-term product sense and vision. Although AI can optimize a product backlog based on historical data patterns, it is not able to create a vision that represents human values or long-term societal trade-offs. Making an engaging story is a human-specific ability from stakeholders' ambiguous needs. It is difficult to decide what should be constructed, as it should be built by a holistic perspective on the market sentiment and organizational purpose, which the current AI cannot replicate (Hussain et al., 2021).

2.6.2 Ethical and Value-Driven Decision Making

Humans are required to be an ethical anchor when ignoring the algorithmic suggestions that might contradict organizational culture or long-term trust. Humans give the final verification and polishing of AI reports to make them agree with the ethics (Stray et al., 2025).

2.6.3 Empathy, Emotions, and Team Dynamics

Human intervention is important to ensure that high-performing Agile teams operate based on psychological safety and trust. The task of the Scrum Master is crucial to read between the lines of emotional signals, e.g., burnout, stress, or conflict under the surface, and to offer coaching (Cobb, 2023).

2.6.4 Creative and Problem-Solving

Human beings are needed to break assumptions and bets in high uncertainty. Human ability provides the possibility to reframe problems when a project faces challenges. Without prior experience, the AI models cannot do it (Hughes et al., 2025).

2.6.5 Leadership and Agile Culture

An agile project is mixed with messy signals, that is, politics, culture and tacit knowledge. Humans are also adept at adapting or neglecting a process, such as modifying a Sprint Goal as a result of some outside event. This involves some level of contextual judgment that has to balance local measures (such as velocity) and wider results (such as customer trust) that cannot be reliably recreated by current AI. In complex engineering scenarios, this is still an important task to be performed by humans(Cinkusz et al., 2024).

Finally, leadership remains a human domain. Research shows that high-performing teams succeed more due to human culture and interpersonal skills than technical tools alone (Asghar & Burria, 2025). The human role is to inspire people and create a culture of continuous learning and psychological safety. Furthermore, Agile transitions are affected by human factors, where motivation, training, and cultural adaptation are factors that define the success of adoption (Gandomani et al., 2020).

2.7 Artificial Intelligence in Project Management Context

Artificial Intelligence (AI) is a general area of computer science that focuses on creating systems that can mimic human intelligence, including learning, reasoning, perception and understanding language (Russell & Norvig, 2016).

AI applications in project management and Agile settings primarily focus on analyzing vast amounts of project data, providing insights, automating repetitive tasks, and assisting in decision-making (Ajibade, 2025; Tominc et al., 2023).

2.7.1 Machine Learning (ML) and Predictive Analytics.

Machine Learning is the core of AI and is based on neural networks to detect patterns in large volumes of historical data that a human project manager might be unaware of. ML is mainly used in predictive analytics in Scrum environments. These systems consider the capacity of historical teams and agility features to predict the sprint velocity, determine the budget overrun, and detect possible risks in the project before they occur (Almalki, 2025). ML creates transparency and trust in the team by presenting data-driven reasons supporting such predictions using methods like SHAP-based models (ForouzeshNejad et al., 2025).

2.7.2 Natural Language Processing (NLP)

NLP is the subdivision of AI that deals with the communication between computer systems and human language. NLP tools are now being employed more in Agile practice to automate artifacts that consume much communication. This involves deriving action items based on the content of daily stand-up transcripts, sentiment analysis of team logs to determine morale, and summarizing stakeholder comments into requirements that can be acted upon. Recent developments use NLP to aid automated validation to enhance the user story vagueness and completeness (Alliata et al., 2025).

2.7.3 Generative AI (GenAI)

In contrast to the classical AI, which is aimed at classification, Generative AI (GenAI), which is operated on the basis of Large Language Models (LLMs) can generate completely new content. GenAI is an important efficiency improvement to the Agile practitioner, who can use it to write user stories based on epics at the high level, to create automated test cases, and to provide summaries of long-form project documentation (Alliata et al., 2025). On the one hand, GenAI can greatly decrease administrative overheads, but a study highlights that it needs to be validated by humans in the loop, as otherwise it would cause hallucinations and make the results of the work correspond to the ethical norms of the team (Stray et al., 2025).

2.7.4 AI Agents (Agentic AI)

AI agents are the most intelligent level of AI integration that goes beyond a fixed kind of tools to act as independent colleagues. Offering LLMs as a reasoning engine, these cognitive agents plan and act, with minimal human supervision. In the Scrum methodology, an AI agent could be used to track a Jira board and automatically assign tasks, schedule work across distributed teams, or propose backlog prioritization, based on real-time information integration (Cinkusz et al., 2024). It makes possible a human-AI symbiosis with the agent engaging in low-level coordination and the human with high-level strategy and interpersonal leadership (Hughes et al., 2025; Stray et al., 2025).

2.8 AI Applications in Agile Project Management

In the field of Agile Project Management (APM), the use of Artificial Intelligence (AI) is a paradigm shift from Information-Based to intuition-based, Manual Administration. The capabilities of AI match the primary Agile areas of performance, particularly the planning, delivery, and uncertainty management (Almalki, 2025; Taboada et al., 2023). Throughout the Agile lifecycle, AI, or more specifically Machine Learning (ML), Natural Language Processing (NLP), and Generative AI (GenAI) are used to stream-line processes such as backlog refinement, sprint retrospectives, and more.

2.8.1 Backlog Management

Traditionally, managing the product backlog is a process that is time-consuming and may be subject to human error, redundancy, and lack of priorities. The automation based on AI addresses these inefficiencies through the use of NLP and ML to process historical sprint information, dependencies between features, and evolving business priorities (Anissa Putri Widodo & Voutama, 2025). GenAI tools have the capability to re-rank tasks dynamically, eliminate redundancies, and produce different user stories, depending on market trends and user responses (Bahi et al., 2024). Moreover, NLP algorithms can help Product Owners to break down complex user stories into smaller tasks, detect the lack of acceptance criteria, and cluster similar ones to prevent duplication, potentially reducing backlog sorting time (Anissa Putri Widodo & Voutama, 2025; Lumbanraja et al., 2024).

2.8.2 Sprint Planning and Estimation.

In Scrum, the estimation techniques commonly used in sprint planning, e.g., planning poker, are also susceptible to cognitive bias and often erratic accuracy (ForouzeshNejad et al., 2025; Tomaz et al., 2026). This step is improved by AI models that substitute human guesses with predictions that are based on statistics. Algorithms consider past velocity, task complexity, and personal developer indicators as important metrics to predict software development time and determine story points with good accuracy (Nabot et al., 2025; Zhang et al., 2024). Besides, GenAI applications (like ChatGPT-based tools) can be used as cognitive partners in planning sessions, providing an effective starting point in team discussions as they automatically subdivide epics into actionable subtasks and indicate the presence of unnoticed technical dependencies (Zhang et al., 2024).

2.8.3 Workload Balancing and Resource Allocation.

Resource efficiency in time-sensitive Agile sprints is crucial, especially in a distributed environment. Task assignment is classically done, which causes an imbalance in workload, resulting in bottlenecks and burnout for developers. Decision support systems run by AI are optimizing their resource management by dynamically assigning tasks to team members according to their real-time availability, past performance, and skill profile (Almalki, 2025; Nabot et al., 2025). AI can constantly check capacity and automatically propose workload reassignments when a team member feels overworked, or the project scopes alter during the current sprint, using sophisticated algorithms such as reinforcement learning and constraint satisfaction (Almalki, 2025; Chapal Barua et al., 2025).

2.8.4 Risk Mitigation

Due to its iterative nature, Agile project management can handle risk, but unforeseen challenges can miss the sprint goals. ML models (including XGBoost and Long Short-Term Memory networks) can be used to predict possible schedule delays, budget overruns, and module failures at the beginning of the development cycle by analyzing the sprint velocity, task statuses, and historical defect rates (Chapal Barua et al., 2025; Nabot et al., 2025). Besides quantitative data, AI can also use NLP-based sentiment analysis to process unstructured data, including meeting transcripts, emails, and chat logs, to identify the emergence of stress, miscommunication, or low morale in the team, allowing Scrum Masters to intervene before the problem can affect the project delivery (Almalki, 2025; Chapal Barua et al., 2025).

2.8.5 Improving Scrum Ceremonies (Execution and Retrospectives)

Within the Sprint Retrospective, the AI chatbots and NLP tools are helpful as they analyze meeting notes, cluster anonymous team feedback into themes, and create detailed summaries (Lumbanraja et al., 2024). The historical data represented and stored in these AI-assisted retrospectives gets input into the predictive models of the system, which contributes to a feedback loop that enhances decision-making and project performance in future sprints (Almalki, 2025; Lumbanraja et al., 2024).

2.8.6 Meeting Summaries Automation

Agile models are based on regular events, including the Daily Scrum, that can be greatly simplified with the help of Artificial Intelligence. NLP and Large Language Models (LLMs) are capable of converting meeting transcripts into summaries that are brief and actionable. Cabrero-Daniel et al. (2024) showed that specialized LLM assistants can track Daily Scrums to summarize issues on the fly, create new tickets, and offer meeting recommendations. This is especially useful with distributed teams. Somanathan (2023) reports that NLP systems can easily identify the important action items in long conversations, reduce miscommunication, and increase team alignment without creating an extra administrative burden.

2.8.7 Reporting and Stakeholder Communication

Project managers and Scrum Masters have been used to devoting much time to administrative duties such as status reporting. This is changed by AI that will automatically create complete project reports and give real-time sprint updates. Gohar (2024) points out that automating stakeholder messages and other routine questions through NLP can help decrease administrative overheads considerably. Furthermore, Generative AI has the ability to retrieve retrospective feedback and create continuous project documentation to facilitate data-driven decision-making (Bahi et al., 2024). Finally, automated reporting systems increase the quality of documentation and release Agile teams to concentrate on strategic, high-value projects instead of manual reporting (Damian & Barbu, 2025).

2.8.8 Summary of AI Capabilities Across the Agile Lifecycle

Table 2. Summary of Selected Studies on AI Tools in Agile Project Management

Agile Activity / Phase	AI Technologies Utilized	Key Impacts and Benefits	Key References
Backlog Management & Refinement	Machine Learning, Generative AI, NLP	Analyzes historical data and dependencies; dynamically reorders tasks; splits complex user stories into granular tasks; reduces refinement time.	(Anissa Putri Widodo & Voutama, 2025; Bahi et al., 2024)
Sprint Planning & Effort Estimation	Predictive Analytics, ML forecasting, GenAI	Eliminates the subjective heuristic guess and makes data-driven predictions, accurately predicts velocity and automatically decomposes epics for team discussion.	Nabot et al. (2024)
Resource Allocation	AI Decision Support Systems, Reinforcement Learning,	Assigns tasks to team members according to their real-time availability, past performances and skill sets; automatically redistributes tasks to avoid bottlenecks and burnout.	Almalki (2025); Barua et al. (2025); Nabot et al. (2024)
Risk Mitigation	ML (XGBoost, LSTM networks), NLP (Sentiment Analysis)	Helps to move risk management from reactive to anticipatory; Identifies schedule/budget delays by forecasting; Identifies early signs of team stress and miscommunication from unstructured data (e.g., chat logs).	Almalki (2025); Barua et al. (2025); Nabot et al. (2024)

Agile Activity / Phase	AI Technologies Utilized	Key Impacts and Benefits	Key References
Scrum Ceremonies (Execution & Retrospectives)	Customized LLMs, AI Chatbots, AI Agent	Gives live feedback during Daily Scrums; tracks compliance with Agile rules; groups anonymous feedback into categories at Retrospectives.	Almalki (2025); Cabrero-Daniel et al. (2024);
Automated Meeting Summaries	NLP, LLM Meeting Assistants	Transcribes meeting notes (spoken and/or written) into actionable items; generates concise summary, extract key action items, ensure alignment, particularly in distributed/virtual teams.	Cabrero-Daniel et al. (2024)
Report Generation & Stakeholder Communication	Generative AI, Automated Data Pipelines	Automatically creates status reports from the real-time information of tools such as Jira; generates documents for sprint review; reduces manual administrative efforts and human errors.	Somanathan (2023)

The reviewed studies show that AI contributes most strongly to data-intensive, repetitive, and prediction-oriented Agile tasks.

2.9 Agile Project Management Performance

Agile project management is primarily used because it helps with adaptability and ongoing delivery of value in a changing environment. Projects are undertaken in short, incremental sprints, with continuous feedback and improvement (Dong et al., 2024). But Agile approaches do not reduce the uncertainty of projects. They deal with it by requiring a constant stream of decisions about project scope, prioritization, and team load (Breyter, 2022).

This constant change means that traditional performance measures do not adequately reflect Agile project performance. For instance, a team may complete software development quickly but experience significant quality issues, or they may complete several features by the due date but not fulfil the stakeholders' requirements. As such, Agile performance can only be evaluated in a multidimensional way, going beyond the traditional "iron triangle" of time, cost, and scope to also consider business value and customer satisfaction (ForouzeshNejad et al., 2025).

Agile performance often depends on the ability of teams to effectively coordinate their efforts and for project managers to make critical decisions under uncertain conditions. Additionally, project performance is greatly improved by the teams' high capabilities, fast learning from previous cycles, and continuous adaptation to change (Koudriachov et al., 2025).

The key performance dimensions of Agile projects vary depending on the project priorities and corporate strategy:

Delivery reliability: This deals with the reliability of the team's work. This includes the sprint completion rate (the percentage of backlog items committed to a sprint and successfully completed) and the variability of the lead time and cycle time (how long it takes for a piece of work to be delivered from initial request to completion) (Breyter, 2022; ForouzeshNejad et al., 2025).

Predictability: Agile is adaptive, but teams still want to be able to forecast. This relates to forecast accuracy and estimation accuracy, which ensures that the team's forecast (often referred to as story points) matches the actual time and effort needed to complete the tasks, without overestimating (Almalki, 2025; Chapal Barua et al., 2025).

Risk handling: In an Agile environment, early identification and effective mitigation of risks are crucial to reducing sprint disruptions. Good risk handling avoids bottlenecks that may disrupt the sprint objectives and may reduce the build-up of technical debt (Almalki, 2025; ForouzeshNejad et al., 2025).

Decision quality: Effective Agile teams are better at making decisions about the product backlog and resource allocation. This means that high-value tasks are prioritized and tasks are allocated to individuals based on capacity and skills (Chapal Barua et al., 2025; Dong et al., 2024).

Team effectiveness: Agile is largely a human interaction-based approach, so teamwork quality and clarity of communication are key. Team effectiveness is determined by trust, shared leadership, and the ability to flexibly coordinate tasks (Dawarka et al., 2025; Koudriachov et al., 2025).

Stakeholder value: The ultimate concern for Agile is customer satisfaction and acceptance. Results in this dimension are enabled by quicker feedback cycles, which ensure the product is in line with the expectations of the stakeholders and evolving business needs (Breyter, 2022).

2.10 Human-AI Collaboration in Agile Project Management

Human-AI collaboration is a concept where AI is used to complement and not substitute human abilities. Here, AI helps in the routine tasks such as generating codes, and the developers use critical judgment to filter and test the results (Stray et al., 2025). Also, human control will be critical in the quality assurance of software. Team-based models are going to take advantage of human domain knowledge to analyze and improve AI-generated test automation summaries, making them accurate, relevant, and aligned with project objectives (Thomas, 2025).

The intentional use of AI in project management needs to be organized to combine machine intelligence with human knowledge to enrich strategic decision-making processes and promote innovation (Hofmann et al., 2020). Surveys of Large Language Models (LLMs) and bespoke meeting assistants in Agile processes highlight the need to govern with a human. Human feedback will be essential to put AI proposals into perspective, address algorithmic biases, and bring the technology in line with the expectations and practices of the team members (Cabrero-Daniel et al., 2024).

Also, the effectiveness of human-AI integration is greatly dependent on the process of trust calibration, a dynamic, socio-technical process in which the team members continuously vary their trust in AI systems to prevent both over-trust (automation bias) and under-utilization. Trust calibration properly restores the interaction in collaboration and enhances overall performance in project teams many times (Dawarka et al., 2025).

2.10.1 Collaboration in Product Backlog Refinement

This process is driven by human input through the negotiation and prioritization of items based on business value, as well as clarifying vague requirements. Product Owners and Agile teams use their expertise and negotiation skills to ensure the backlog items remain aligned to business strategy and ethics (Cobb, 2023).

AI helps this step by working behind the scenes to review past data, recommend user stories, identify task interdependencies, spot duplicates, and propose acceptance criteria (Zhang et al., 2024). Large language models (LLMs) can also be used as agents to automatically refine the quality of user stories in the backlog to ensure they are well understood and aligned to business goals in advance of the sprint starting (Zhang et al., 2024). Human-AI collaboration occurs when AI agents make these data-informed suggestions and human users validate and improve them. This approach has been empirically demonstrated to shorten the backlog refinement process by 55% to 60%, enabling the development team to reduce manual effort in sorting and prioritizing and focus on creating valuable features while maintaining strategic alignment (Anissa Putri Widodo & Voutama, 2025).

2.10.2 Collaboration in Sprint Planning

Humans are the ones who are responsible for sprint goal setting and capacity planning and commit to them based on their experience and team dynamics (Dawarka et al., 2025). AI can assist this process by moving teams away from intuition-based towards data-driven task and workload forecasting. AI forecasts the velocity of past sprints, recognizes potential dangers, recommends achievable sprint ranges and automatically splits epics and user stories into smaller tasks. The research findings are truly remarkable, with an AI-driven task allocation boost of 70% in accuracy, resulting in a more effective distribution of tasks and overcoming sprint bottlenecks (Anissa Putri Widodo & Voutama, 2025). Human-AI collaboration involves situations where the human user makes a decision using AI's data-driven prediction and specific contextual factors, like team morale, psychological safety, or unforeseen external factors (Hughes et al., 2025).

2.10.3 Collaboration in Daily Scrum (Stand-up)

This brief meeting is based on human communication, trust, and rapid decision-making to provide transparency and connect the development tasks to a higher goal (Hussain et al., 2021). Scrum Masters guide the conversation and help clear impediments. This meeting can be assisted by AI technologies that use natural language processing (NLP) to analyze the notes from stand-up meetings and identify recurring impediments, then generate high-quality reports or tickets with short updates on work progress. Collaboration between AI and humans should be based on AI gathering the data and real-time suggestions, and humans on discussion and decision-making. To avoid the meeting being perceived as overly robotic and negative, AI should inform and suggest rather than warn and command the meeting (Cabrero-Daniel et al., 2024).

2.10.4 Collaboration in Sprint Execution

Team members and programmers develop technical, creative, and problem-solving abilities. AI is particularly adept at generating code snippets, performing automated testing, identifying bugs, and suggesting code optimizations (Stray et al., 2025). However, human involvement is crucial to ensure quality, ethical implications, and compliance with non-functional requirements (e.g., security, reliability, and portability).

2.10.5 Collaboration in Sprint Review

The team and stakeholders work together to demonstrate and seek feedback on increments, employing human communication skills and social intelligence to openly discuss progress and areas for improvement (Cobb, 2023). AI can help in creating visual summaries, metrics dashboards, and progress summaries. AI-powered dashboards now offer support in the form of natural language generation (NLG), which automatically summarizes the data in a format intelligible to stakeholders and supplements charts (ForouzeshNejad et al., 2025; Ajibade, 2025). AI's ability to provide this real-time information, which is usable and interpretable by humans, and can be shared with stakeholders, enhances collaboration while communicating data insights and business understanding to inform better adaptations (Ajibade, 2025).

2.10.6 Collaboration in Sprint Retrospective

This process is completely reliant on human transparency, psychological safety, and learning (Hussain et al., 2021). Improvements are identified through open discussions. AI can help here with anonymous feedback, machine learning to group discussion items into clusters, sentiment analysis of team communications, and highlighting cross-sprint data patterns (Ajibade, 2025). The best practice is to combine AI solutions that provide insights (such as predictions on team velocity and issue classifications) with human discussion that leads to effective improvements for subsequent sprints (Elumalai, 2025).

2.10.7 Summary and Human- AI Collaboration

Table 3. Performance Metrics and Purpose (Adapted from selected articles)

Metric	**Definition**	**Purpose**	**Human-AI Collaboration**
Velocity	Story points completed per sprint	Measures team capacity and predictability	AI can forecast velocity; humans interpret contextual factors
Sprint Burn Down Chart	Remaining work vs. Time left in sprint	Tracks daily progress and identifies delays	AI generates real-time charts; humans address blockers
Cycle Time	Time from work start to completion	Identifies workflow bottlenecks	AI tracks automatically; humans reduce waste
Lead Time	Time from request to delivery	Assesses end-to-end responsiveness	AI predicts delays; humans prioritise
Cumulative Flow Diagram	Visualises work in different states over time	Reveals bottlenecks and process health	AI updates dynamically; humans analyse root causes
Team Satisfaction	Surveys or retrospective scores	Evaluates well-being and collaboration	AI analyses sentiment; humans build trust
Business Value Delivered	Stakeholder-rated value of completed features	Links output to business impact	Humans define value; AI quantifies trends

2.11 Challenges and Risks of AI Implementation in APM

There is a lot of potential in applying Artificial Intelligence (AI) to Agile Project Management. It also shows a complicated situation with technical, organizational and ethical aspects. Unless properly dealt with, these risks can impact Agile processes, erode team trust, and ultimately affect project results.

2.11.1 Data Quality, Privacy, and Security

The success of AI and machine learning algorithms in APM depends on the presence of large, quality past data (Almalki, 2025). The unfinished, old-fashioned, or uncoordinated data may provide inaccurate predictive analytics, incorrect effort estimations, and incorrect task priorities (Khoulenjani et al., 2024; Somanathan, 2023). Moreover, the processing of sensitive project information, team performance measurements, and internal communication logs is associated with high privacy and security concerns. Strict data protection laws, like GDPR, are not to be compromised. It has been found that 60 percent of the executives mention data security as a leading concern when adopting AI tools because improper data management can result in dire legal and financial consequences (Tupsakhare, 2022).

2.11.2 Complexity of Integration

Bringing the current AI solutions to the existing Agile workflows and legacy project management software is a significant technical obstacle. Most organizations use older and inflexible systems that have not been built to allow real-time AI analytics, cloud services, and complex API-driven data flows (Jain & Butler, 2024). The process of ensuring that AI tools are compatible with the already existing continuous integration/continuous deployment (CI/CD) pipelines may be a very complicated one (Frank, 2024). As a result, to implement a smooth integration, it is crucial to spend a lot of money, upgrade infrastructure, and acquire special technical skills, which are often absent in the existing project teams (Almalki, 2025; Tupsakhare, 2022).

2.11.3 Cultural Resistance and Workforce Adaptation

The human aspect and group dynamics can be considered one of the most difficult barriers to the adoption of AI. AI is perceived as a threat or an encroachment by team members who are used to traditional Agile practices and as a danger to their job security, which results in cultural resistance (Hamza et al., 2025; Mogbojuri et al., 2025). Such hesitation is intimately connected with the issue of the calibration of trust. Teams can under- or over-trust AI by ignoring AI evidence in favor of human intuition or ignoring AI results (automation bias), respectively, leading to a failure to identify system errors in high-stakes situations (Dawarka et al., 2025). Moreover, though AI tools simplify business, excessive automation may destroy informal communication, including ad-hoc reports and social signals, that help to build a common understanding and group cohesion in Agile environments (Dawarka et al., 2025).

2.11.4 Algorithms, Bias, and Explainability

The use of AI in APM is associated with complicated ethical issues, especially when it comes to algorithmic fairness and transparency (Hughes et al., 2025). The biased historical data used to train AI models can unknowingly reproduce discrimination, resulting in unfair distribution of tasks and biased performance (Nabot et al., 2025).

Also, explainability is constrained by the black-boxed nature of advanced deep learning and Large Language Models (LLMs). Unless they can grasp the logic behind these recommendations, agile teams might be reluctant to trust or act on AI-generated recommendations (Cinkusz et al., 2024). Researchers highlight the need to implement explainable AI (XAI) methods and have a "Human-in-the-Loop" (HITL) governance framework to reduce these risks. This will ensure that AI serves as a tool to assist, advise, but not supplant, the human practitioner and that the human practitioner is accountable and makes the final decision and ethical judgments (Chapal Barua et al., 2025).

2.12 Strategies to Overcome Challenges and Risks

Artificial Intelligence has the potential to be effectively utilized in Agile Project Management. Organizations need to expect and address technical, cultural, and ethical problems. The literature implies that there is a holistic approach that is centred on data governance, incremental implementation, training employees, and ethical considerations.

2.12.1 Establishing Secure Data Governance and Security

To address concerns of data quality and confidentiality, companies need to develop robust data governance policies (Wirtz et al., 2022). Robust authentication, encryption and anonymization of data must be implemented to secure the data of the project and comply with privacy laws such as the General Data Protection Regulation (GDPR) (Cinkusz et al., 2024). Moreover, given that AI algorithms are data-dependent, data cleaning, standardization, and continuous updates of historical and real-time data prior to AI deployment is vital to ensure the consistency and accuracy of the AI predictions (Whang et al., 2023).

2.12.2 Phased Adoption and Testing

However, the technical difficulties associated with implementing new AI tools and integrating them into existing systems can be overcome through an incremental approach (Tupsakhare, 2022). Rather than a disruptive "big bang" approach, Agile teams should begin to incorporate AI into specific and low-risk sections of the continuous integration/continuous deployment (CI/CD) pipeline or Agile process, for example, automated testing or backlog prioritization (Tupsakhare, 2022). Trial projects can be used to evaluate tool integration, plan integration strategies, and get teams up to speed with AI tools without disrupting current work (Stray et al., 2025).

2.12.3 Change Management and Upskilling

To counteract cultural and workforce resistance, change management strategies that promote a collaborative and Agile culture are important (Tupsakhare, 2022). An early stakeholder engagement is required to communicate the rationale for introducing AI technologies, as they are not meant to replace human labour but to complement and automate repetitive admin tasks (Saklamaeva & Pavlič, 2023). At the same time, there should be strong training and skills-building programs; ensuring that team members are equipped with the necessary AI literacy and technical skills enables them to effectively leverage AI tools and understand the results produced by data analyses (Hughes et al., 2025).

2.12.4 Explainable AI and Human-in-the-Loop Governance

Change management is important to overcome cultural and work force resistance as it fosters a culture of collaboration and Agility (Tupsakhare, 2022). An initial stakeholder engagement is needed to explain why AI technologies are being introduced, as it is not to replace human work; it is meant to complement and automate repetitive admin tasks (Saklamaeva & Pavlič, 2023). At the same time, there should be strong training and skills building programs; ensuring that team members are equipped with the necessary AI literacy and technical skills enables them to effectively leverage AI tools and understand the results produced by data analyses (Hughes et al., 2025).

2.12.5 Summary of Overcome Challenges

Table 4. Strategy to Overcome Challenges of implementing AI tools

Challenges	**Strategy to overcome**
Data Quality Issues	High-quality data and robust governance.
Team Resistance	Training and regular team discussions.
Lack of Trust	Implementation of Explainable AI (XAI).
"Black-Box" Risks	Human-in-the-loop and final oversight.
Integration Complexity	Phased integration approach and infrastructure upgrades.

2.13 Synthesis and Research Gaps

The selected literature confirms that Agile Project Management is based upon human-centric principles, whereas AI can provide strong augmentation. Efficiency and prediction gain always come with research, but there is always a gap: most research is done on the work of AI or human factors alone and not together. Existing definitions of Agile performance still include multi-dimensional measures, like adaptability or team well-being. Furthermore, little research has been conducted to provide models for practitioners to balance automation and human judgment in real Agile environments.

To fill this gap, the thesis will discuss how AI and human tools can work together to enhance Agile performance by analyzing data from practitioners. The methodology, empirical results, and a proposed conceptual framework for effective human-AI collaboration are presented in the following chapters.

3 Methodology

This chapter explains the research philosophy, research approach, research design, data collection, sampling, operationalisation, data analysis, validity, reliability, ethics, and limitations of the methodology. Every methodological choice was designed to answer the research question: How does the collaboration of Human and Artificial Intelligence improve performance in Agile project management?

3.1 Research Philosophy

This research is based on the philosophical framework of positivism. Positivism assumes that knowledge is created by using objective, measurable, and observable data (Saunders et al., 2023). It is the best-suited philosophy for quantitative research as it is based on the premise that there is a reality that can be measured systematically and that results can be generalized for similar contexts.

This thesis could be written in a positivist style for two reasons. The first is that the research questions are based on measurable perceptions and patterns, for example, the use of AI tools in activities related to Agile and practitioners' perceptions of how these affect project performance. Second, this thesis aims to find clear patterns and associations in a sample of Agile practitioners, and this relies on structured and standardised data collection, not subjectively.

3.2 Research Approach

The approach used in this study is deductive research. Deductive reasoning begins with existing theory and literature and then determines whether this theory is validated by empirical data (Saunders et al., 2023). The literature review in this thesis was used to guide the design of the survey instrument, the variables being measured and to inform the development of the variables.

The deductive approach was suitable, as the major concepts of the use of AI tools, the role of the human being, the impact of collaboration, and the challenges are well established in the literature. The survey was aimed at verifying the findings from the literature that experiences of practitioners in real Agile environments align with what is suggested.

3.3 Research Design

The research design was an explanatory cross-sectional survey. The cross-sectional design was suitable because it allowed data collection with a standardized questionnaire from geographically distributed Agile practitioners during a set time period (Saunders et al., 2023). This design was appropriate because:

- It allows data collection from geographically distributed Agile practitioners.
- It produces structured, comparable data that can be analysed statistically.
- It is widely used in Agile and information systems research to measure practitioner perceptions (Kwasek et al., 2025).

The quantitative part involved multiple-choice questions and Likert items (1 = Strongly Disagree to 5 = Strongly Agree). These question types produce numerical data that can be analyzed using descriptive statistics and correlation analysis.

3.4 Data Collection

The study used primary data collected via a structured questionnaire using Google Forms. Data collection through surveys is suitable when a set of standardized information is needed from a range of respondents across various locations and organizations

(Saunders et al., 2023). The survey was designed to take 10-12 minutes to complete and was shared via professional networks: LinkedIn, Agile project management related groups, searching for people who are related to agile teams from previous working places, and university contacts. It was an anonymous and voluntary questionnaire. The consent section at the beginning of the survey outlines the purpose of the study, that participation was voluntary, and that no sensitive information of the organization and customers should be disclosed.

The questionnaire was structured into Five sections:

Section 1 - Personal Information: Role, Agile and Scrum experience, industry, firm size, country of work, and self-reported AI knowledge. This allowed for subgroup analysis and for interpretation in terms of practitioner characteristics.

Section 2 - AI Tools Used in Agile project management activities: Reveals the types of AI tools in use (e.g., generative AI tools, predictive analytics, automated reporting, meeting summaries, and AI-integrated project management platforms), how often they are used, and in what Agile project management ceremonies. Items are informed by Saklamaeva and Pavlič (2024).

Section 3: Human Judgement and Leadership in Agile Project Management: Assesses the role and indispensability of human judgement, leadership, stakeholder management, creative problem solving and ethical governance in Scrum. Items are informed by Hoda et al. (2023) and Koudriachov et al. (2025).

Section 4 - Humans and AI Collaboration and Agile Performance: Measures level of practitioner agreement (1 = Strongly disagree, 5 = Strongly agree) with the following: (i) operational performance (predictability of sprints, speed of reporting, task estimates, reliability of delivery); (ii) decision performance (quality of prioritization, awareness of risks, adaptation to change); and (iii) team performance (communication, collaboration, balance of workload, team morale). Items are inspired by ForouzeshNejad et al. (2025).

Section 5 - Challenges, Trust, and AI Governance: Measures concerns related to AI reliability, transparency, bias, data privacy, over-reliance, and organizational resistance to AI adoption. Items are informed by Akhiwu (2025) and Cinkusz et al. (2025).

The questionnaire was pre-tested with five Agile practitioners and academic colleagues to ensure clarity of questions, sufficiency of response options, and completion time. The questionnaire items were subsequently revised. This follows the best practice advice for questionnaire design (Saunders et al., 2023) and enhances face validity and user experience.

3.5 Sampling Strategy

The population of interest was Agile professionals who were currently engaged in Agile-based projects, such as in software, technology, health, marketing, finance, and engineering industries. The role included Scrum Masters, Product Owners, Project Managers, Agile Coaches, Developers, Analysts, Engineers, Team Leads, and so on. Participants must have some experience with APM and some experience with AI tools used in agile project management. This was an appropriate population because the research question is about the real interactions between AI tools and humans.

The surveying was conducted by using a purposive sampling method which ensured that the respondents were acquainted with the topic of the survey so that they could answer the questions. Random sampling was not considered as the study needs participants who are familiar with the Agile ceremonies, Sprint Planning, Sprint execution, and how the AI tools will behave during the project. The process was supplemented with snowball sampling whereby respondents were asked to refer others who had similar qualifications to the survey. This enabled an engagement with Agile practitioners in more specialized roles who weren't possible through direct network distribution.

At least 50-80 surveys were used as the sample size. It was felt that this number of samples was sufficient for the intended quantitative analysis and descriptive statistics as well as simple correlation analysis. Any responses that did not meet the inclusion criteria were removed from the analysis.

3.6 Data Analysis

Descriptive statistics and correlation analysis were used to analyze all quantitative data. Microsoft Excel and Python were used for the analysis. The pandas library was used to manipulate and get descriptive statistics, the numpy library was used for numerical calculations, the scipy.stats library for Pearson correlation and significance testing, and the library pingouin for Cronbach's alpha. To ensure full transparency and reproducibility, Python has been selected because the entire analysis script is provided in Appendix 2, allowing each of the results that are presented in this chapter to be verified independently.

3.6.1 Descriptive Statistics

The characteristics of the sample and main variables were summarized and described using descriptive statistics. Specifically:

- For categorical variables (e.g., respondent role, industry, team size, AI tools used, Agile activities where AI is used), frequencies and percentages were used.
- All Likert scale items were described in terms of their central tendency and spread by means and standard deviations.

Descriptive statistics provided an overall picture of the data patterns and comparisons between the groups of respondents.

3.6.2 Cross-Tabulation Analysis

To compare the answers by different subgroups (Scrum Master, Product Owner, Developer, years of experience), the cross-tabulation approach was used. This can provide insight into whether there are differences in perceptions of human–AI partnership and performance by the respondent's background. It can be used, for instance, to compare whether Scrum Masters and Developers have different views on AI challenges.

3.6.3 Correlation Analysis

Relationships between key variables were analyzed using correlation analysis. In particular, this examined whether increased use of AI tools was linked to increased perceived project performance and if increased human oversight was linked to decreased perceived challenges. These are exploratory correlations; the validity of the results of these correlations is limited by the non-random sampling and self-reported data.

Pearson's r and two-tailed p-values were calculated using scipy.stats.pearsonr(), with significance confirmed via the t-statistic $t = r\sqrt{(N-2)} / \sqrt{(1-r^2)}$ at $df = N-2$.

3.7 Validity and Reliability

The questions were designed to accurately measure the theoretical constructs studied in each survey section, with each section aligned with clearly defined concepts from the literature.

- Content Validity: The survey questions were based on established research related to AI in Agile project management to ensure they are measuring what they are supposed to measure.
- Construct Validity: Each section of the survey was aligned with clear definitions to ensure the questions accurately reflect the concepts being studied.
- Face Validity: The survey was tested in a pilot study before distribution to ensure the questions were clear and easy to understand.
- Internal Consistency: Cronbach's alpha was used to check if the survey questions are consistently measuring the same thing, with a value of 0.70 or higher considered acceptable.
- Reliability: The survey followed a standard format, meaning all participants answered the same questions in the same order to ensure consistency.

3.8 Ethical Considerations

This study adheres to the ethics of voluntary involvement, informed consent, anonymity, confidentiality, and data management. Survey respondents were provided with information about the study. They were told they could choose not to answer any questions and that no questions required them to reveal confidential information about their organization.

That question was not a request for names, employers' names, or personal identifiers. The findings were reported in aggregate. Responses were anonymized in the thesis, so no individual or organization is identified. The data was securely stored and used only for this thesis.

But as the survey is about AI use, trust, and project management practices, participants were asked not to include confidential company information, client names, or project information in their open-ended responses. The study also complied with GDPR principles, as the data collected will only be used for the academic thesis purpose.

3.9 Methodological Limitations

There are some limitations to this study.

1. First, the results are self-reported, which could lead to over- or under-estimating the effects of AI on Agile project management.
2. Second, this study is cross-sectional, meaning it reflects perceptions at a single point in time, and so does not assess long-term impact.
3. Third, the purposive and snowball sampling method means the results might not be generalizable to all Agile practitioners.
4. Fourth, because AI tools are rapidly changing, the findings may need to be revised as new tools and approaches are developed.
5. Finally, the study does not involve experimental use of AI tools in organizations, but instead, how practitioners perceive and interpret AI use in Agile projects.

However, this approach is still appropriate because it fills the research gap: how AI tools and human expertise interrelate in Agile project management.

3.10 Summary of Methodology

Table 5. Methodological Choices and Justifications.

Methodological Elements	**Decision Made**	**Justification**
Research Philosophy	Positivism	Supports objective, measurable data collection and pattern identification (Creswell & Plano Clark, 2023; Saunders et al., 2023)
Research Approach	deductive	Test existing theoretical concepts from literature using structured survey data.

Methodological Elements	**Decision Made**	**Justification**
Research Design	Quantitative cross-sectional survey	Efficient, standard data collection from distributed Agile practitioners.
Primary Data	Structured online questionnaire (Google Form)	Standardised, anonymous access for geographically dispersed Agile practitioners.
Question Type	multiple choice, Likert-scale (1-5)	Produces numerical data suitable for statistical analysis.
Sampling	Purposive + snowball sampling	Ensures domain expertise (Agile + AI)
Target Sample	Min. 50-80 completed responses	Appropriate for descriptive statistics and correlation analysis.
Quantitative Analysis	Descriptive statistics, cross-tabulation, Pearson correlation — Python	Identify patterns and associations across role, experience, and sector subgroups (Saunders et al., 2023)
Validity & Trustworthiness	Content, construct, face validity; Cronbach's $\alpha \geq 0.70$	Ensures measurement accuracy and internal consistency.
Ethics	TENK (2023), GDPR (2016/679), informed consent, anonymity, secure storage	Protects participants; complies with Finnish and EU regulations.

4 Results

This chapter presents the results of the cross-sectional survey of the Agile practitioners to address the main research question and research objectives. It starts by providing an overview of the respondent profile, moves on to the findings on how practitioners are using AI tools, their perceptions of the role of humans in the process, the effect of human-AI collaboration on Agile performance, and concludes with an exploration of the challenges of AI adoption and how practitioners are overcoming them.

This analysis is based on 54 usable responses from the survey. The data were analysed using descriptive statistics, reliability, correlation, and cross-tabulation. The results are presented in a simple analytical style, with the help of graphs, tables, and short explanations.

4.1 Respondent profile

The first part of the survey collected background information about the respondents. This information helps explain the findings' context.

4.1.1 Respondent role

Table 6. Respondent role (N = 54)

Role	Count	Percentage (%)
Scrum Master	14	25.9%
Project Manager	13	24.1%
Team member / Developer / Engineer / Tester	8	14.8%
Project Coordinator	8	14.8%

Role	Count	Percentage (%)
Product Owner	4	7.4%
Team Lead	3	5.6%
Agile Coach	3	5.6%
Analyst	1	1.9%

All respondents worked directly in Agile project management. The biggest groups consisted of Scrum Masters (25.9%) and Project Managers (24.1%). This is useful for studying these roles as they typically participate in the planning, coordination, communication, and decision-making of the sprint.

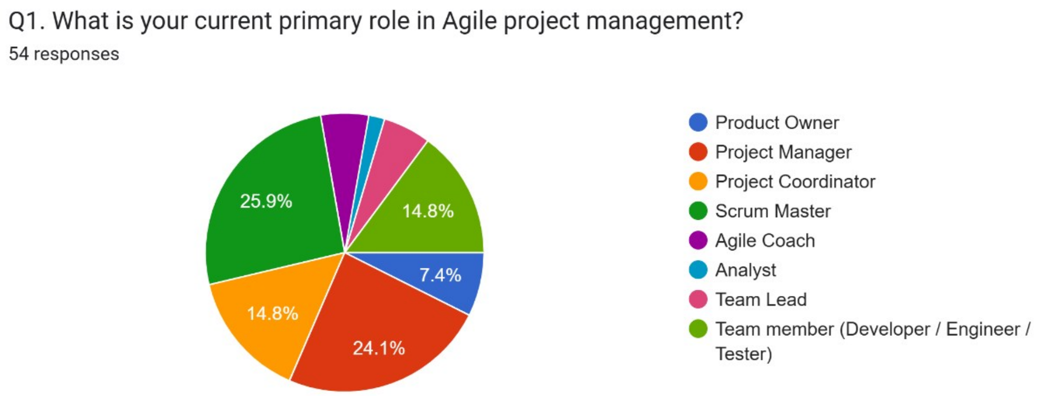

Figure 4. Pie chart of respondents' current working role

4.1.2 Years of experience in Agile Project Management

Table 7. Experience in Agile Project management

Experience	Count	Percentage (%)
4–6 years	18	33.3%
7–10 years	17	31.5%
1–3 years	12	22.2%

Experience	Count	Percentage (%)
More than 10 years	5	9.3%
Less than 1 year	2	3.7%

Among all respondents, 64.8% had experienced Agile for 4 to 10 years. This implies that the information is largely the opinions of people who have already had some hands-on experience of Agile work.

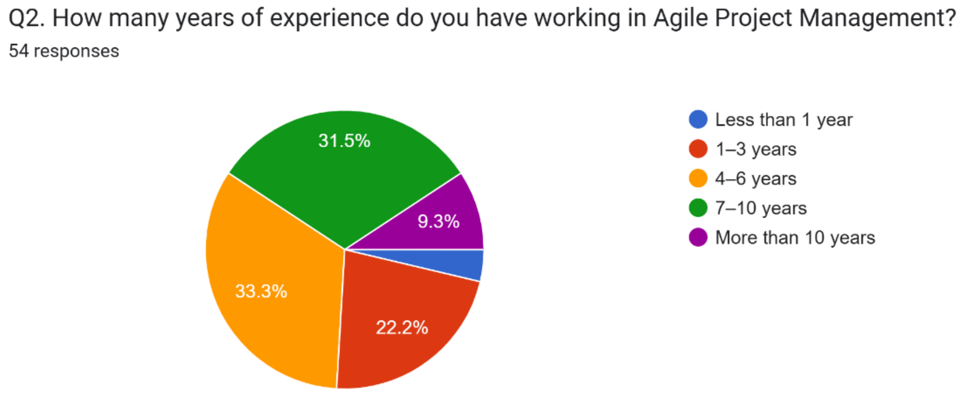

Figure 5. Respondent Experience level from survey

4.1.3 Respondent Working Industry

Table 8. Working Industry

Industry	Count	Percentage (%)
Software / Technology / IT	38	70.4%
Manufacturing / Engineering	10	18.5%
Construction	2	3.7%
Engineering / Manufacturing Industry	2	3.7%
Aviation	1	1.9%

Industry	Count	Percentage (%)
Consulting / Professional Services	1	1.9%

The top working sectors were software, technology, and IT (70.4%). This is to be expected, as Agile and AI tools are often employed in software projects. Yet some other industries are seeing Agile spreading as well, including engineering, construction, aviation, and consulting.

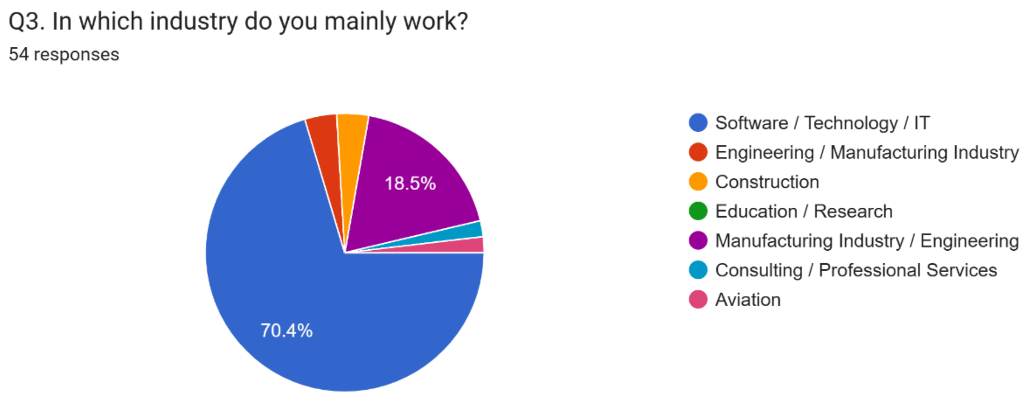

Figure 6. Respondents working in industries from the survey

4.1.4 Team size

Table 9. Team Size

Team Size	Count	Percentage (%)
6–10 people	22	40.7%
Fewer than 5 people	9	16.7%
11–15 people	9	16.7%
More than 20 people	8	14.8%
16–20 people	6	11.1%

A majority of the respondents were organized into groups of 6-10 members. This is near the typical size of most Agile and Scrum teams. It also implies that the results are highly correlated with the Agile practices employed at the team level.

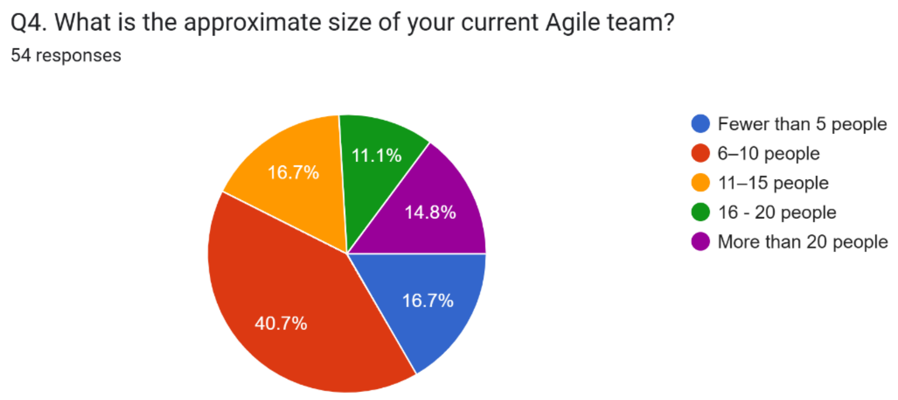

Figure 7. Team size of the respondent from survey

4.1.5 Team location

As far as geographical representation, the distribution was wide, ranging from multiple countries with a presence, such as Bangladesh (33.3%), India (20.4%), USA (20.4%) and Finland (14.8%), which helped bring an international perspective to the AI usage in an Agile environment.

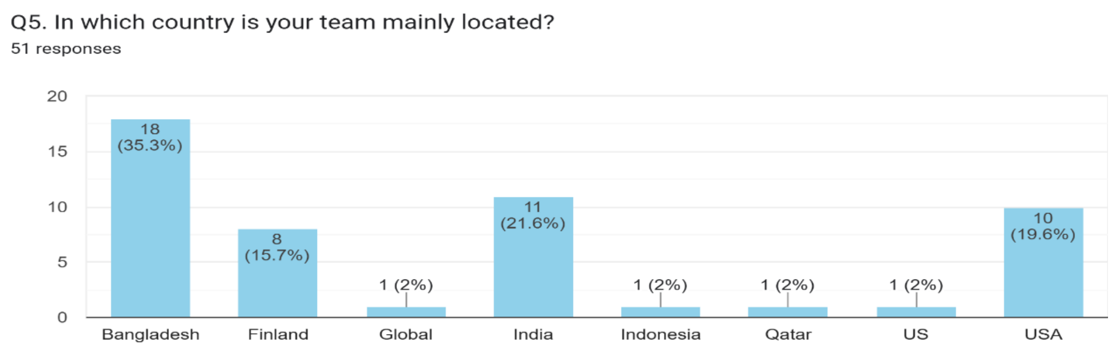

Figure 8. Team location from survey

4.1.6 Familiarity level of AI

Table 10. Familiarity level of AI

Familiarity level	Count	Percentage (%)
Very familiar	28	51.9%
Moderately familiar	15	27.8%
Expert level	6	11.1%
Slightly familiar	4	7.4%
Not familiar at all	1	1.9%

Notably, 63.0% of respondents described themselves as either very familiar or at expert level with AI tools, and a further 27.8% as moderately familiar. Only one respondent reported no AI familiarity. This indicates a generally AI-literate sample that is well suited to give meaningful assessments.

4.2 AI tool use in Agile project management

4.2.1 Agile Activities Where AI Is Used

The respondents were asked to check all the Agile activities in which they are currently using AI tools (Q7). Team communication is the activity that was most frequently facilitated using AI (70.4%, n = 38), followed by sprint planning (68.5%, n = 37) and backlog management (63.0%, n = 34), as demonstrated in Table 7. As the lifecycle progressed, the support or action tracking of daily stand-ups was reported by 61.1% of respondents, and stakeholder communication by 57.4%. About half of the sample used risk identification and monitoring (51.9%) and decision-support tasks (48.1%). Sprint retrospectives and continuous improvement were the least common AI-supported activity (46.3%), but still popular. One person (1.9%) said they used AI in none of these activities.

Table 11. Agile project management activities where AI is used

Agile project management activities	**Count**	**Percentage (%)**
Team communication	38	70.4%
Sprint planning	37	68.5%
Backlog management	34	63.0%
Daily stand-up/action tracking	33	61.1%
Stakeholder communication	31	57.4%
Risk identification and monitoring	28	51.9%
Decision-support tasks	26	48.1%
Sprint retrospective/continuous improvement	25	46.3%
None of the above	1	1.9%

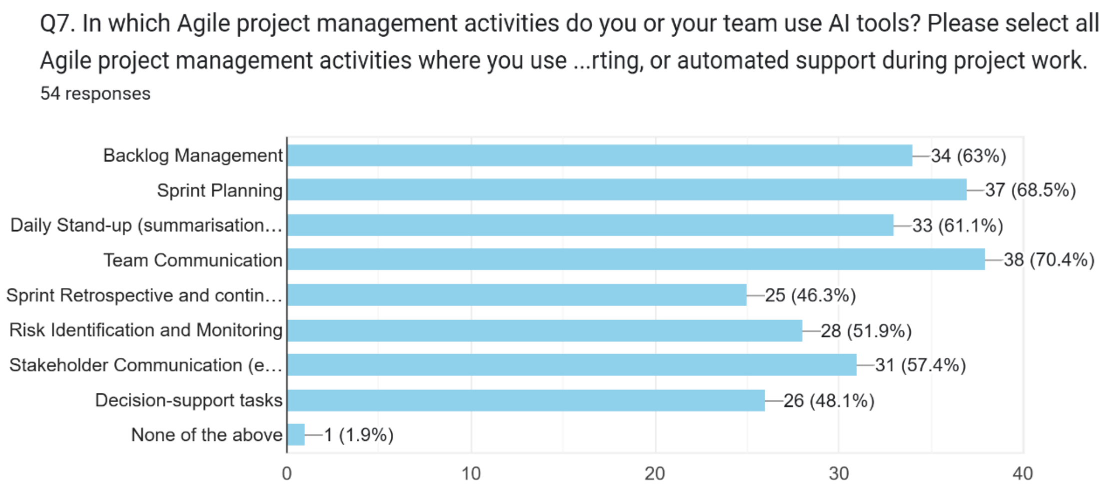

Figure 9. Agile project management activities where AI is used: Chart from survey

4.2.2 AI Tools and Features Used

When it came to the specific tools being used, generative AI assistants – ChatGPT, GitHub Copilot, Gemini, and Claude – were the most widely used type of tool (87.0% of users). Project management software with AI features like Jira and ClickUp was similarly popular (83.3%, n = 45). Other key applications mentioned by the respondents include meeting summarization and transcription tools (68.5%, n = 37) and AI analytics dashboards/reports (53.7%, n = 29). Otherwise, about half of the sample used AI agents for task automation (48.1%) or AI tools for risk or dependency detection (44.4%). The automated backlog prioritization tools, on the other hand, were less common, with only 13.0% (n = 7) found in Agile teams, indicating that highly specialized AI capabilities are still at a relatively early stage of adoption in Agile teams.

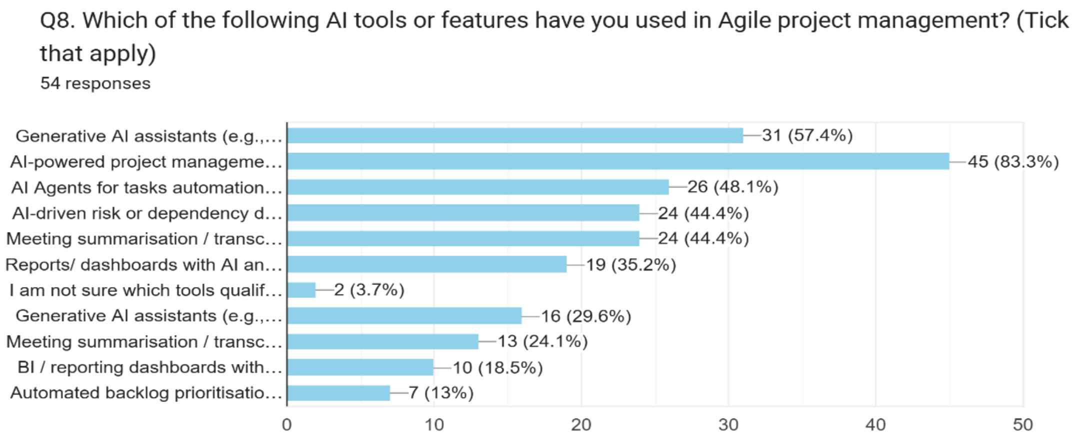

Figure 10. AI tools and features used: Chart from survey

4.2.3 Purpose of AI Use

It is essential to grasp the ‘why' behind the use of AI in Agile practices. The most common reasons were improving communication (79.6%, n = 43) and speeding up routine tasks (87.0%, n = 47) as reported in Q9. The two were both mentioned 75.9% (n = 41) of the time when considering improving estimation and planning and when creating reports/summaries. In addition, the most frequently mentioned goals were: To make better decisions (68.5%), to enhance team productivity (64.8%) and to detect risks in a timely fashion (55.6%). The less common prioritization (42.6%, n = 23) corroborates this hypothesis. Overall, the results align with other studies of the use of artificial intelligence in Agile contexts, as practitioners seem to be using AI mainly for productivity and efficiency purposes (Hughes et al., 2025), such as to minimize administrative work and speed up information processing rather than for any specific, specialized function.

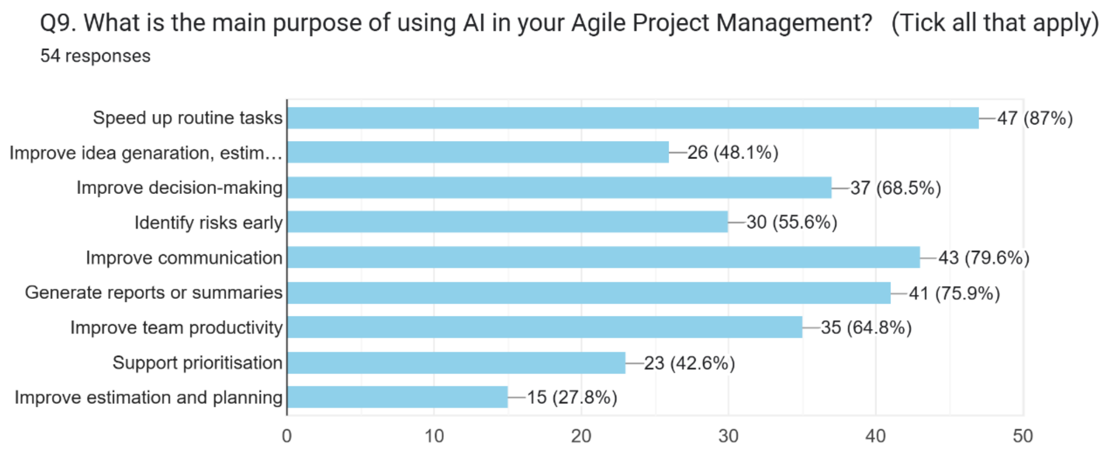

Figure 11. Purpose of using AI tools: bar chart from survey

4.3 Human role in Agile project management

The survey also captured the attitude of respondents regarding the ongoing role of humans in Agile project management. Agreement is very high on the need for human expertise.

Section 3 of the survey (Q10) presented five Likert-scale statements on this topic. All responses were recorded on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree). Table 12 presents the item-level descriptive statistics.

Table 12. Descriptive Statistics: Human role in agile project management

Question Items	**Count(N)**	**Mean**	**SD**	**Agree %**
Human judgment is essential even when AI provides recommendations	54	4.74	0.52	96.3%
Leadership and team motivation remain primarily a human responsibility	53	4.81	0.39	100.0%
Contextual understanding and stake-holder negotiation require human in-volvement	54	4.65	0.68	88.9%
Creative problem-solving in uncertain situations depends on human expertise	54	4.52	0.79	90.7%
Ethical and value-based decisions re-quire human oversight	54	4.80	0.45	98.1%
Construct mean (Cronbach α = 0.803)	54	4.70	0.46	—

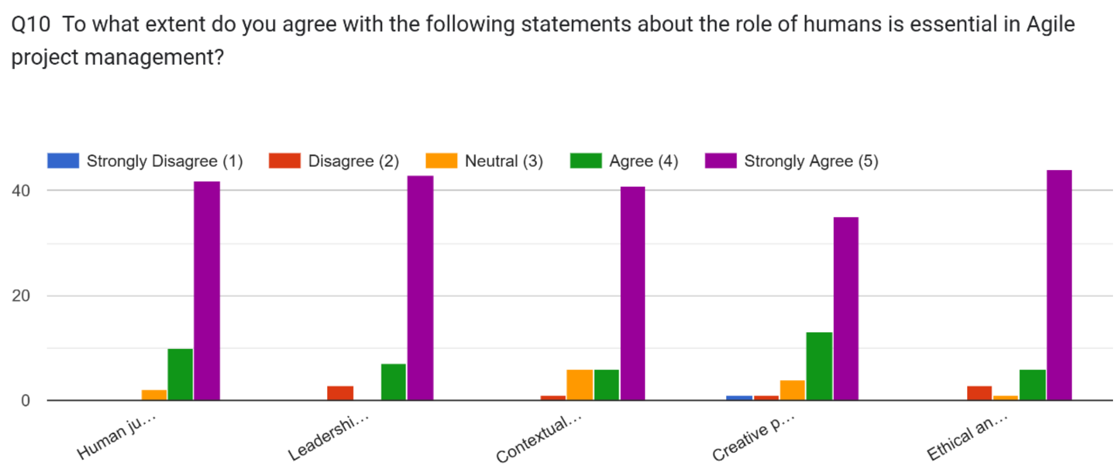

Figure 12. Essential human role in agile project management from survey

There was very high agreement on all five items, with all mean scores being greater than 4.60. Ethical and value-based decisions (M = 4.81) was the most positively rated item in the entire survey, with 100.0% of those who responded to it, (valid responses), agreeing or strongly agreeing (no one disagreed). Creative problem-solving (M = 4.80) was also endorsed by 98.1% of respondents, while leadership and team motivation (M = 4.74) was endorsed by 96.3% of the respondents. The lowest rated item, stakeholder negotiation (M = 4.52) still had a 90.7% agreement. The construct exhibited good internal consistency (Cronbach α = 0.803) and a mean score of 4.70 / 5. The findings not only suggest that the human role is seen as irreplaceable in the Agile approach, but also that it is considered irreplaceable across all Agile teams regardless of their level of AI tool usage.

4.4 Human-AI collaboration and Agile performance

The results from the human role findings are followed by the next section of the survey (Q11) which asks whether practitioners believe that Human–AI collaboration is indeed having a positive impact on project performance in Agile projects. The seven performances were evaluated on a five-point Likert scale. All responses were recorded on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree). Table 13 presents the item-level descriptive statistics. The item-level results are summarised in table 13.

Table 13. Human–AI collaboration impact on Agile project performance

Performance Items	**Count(N)**	**Mean**	**SD**	**Agree %**
Human–AI collaboration enhances overall Agile project performance	54	4.52	0.82	88.9%
Improves communication and transparency within the Agile team	54	4.44	0.74	85.2%
Human judgment combined with AI improves project decision-making	53	4.40	0.72	86.8%
Improves product backlog refinement and prioritisation	54	4.37	0.83	87.0%

Performance Items	Count(N)	Mean	SD	Agree %
AI tools help the team allocate tasks and resources more effectively	54	4.37	0.92	79.6%
AI insights help sprint planning and delivery predictability	54	4.33	0.91	79.6%
AI helps identify project risks earlier	54	4.22	0.90	77.8%
Construct mean (Cronbach α = 0.908)	54	4.38	0.67	—

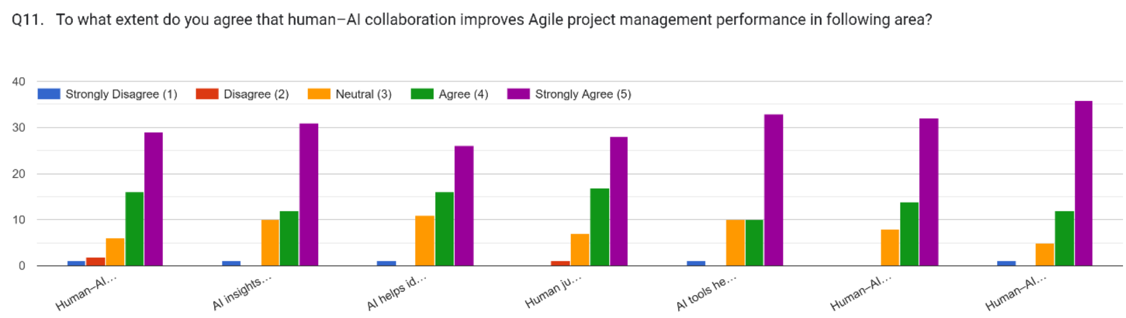

Figure 13. Human–AI collaboration and performance items from the survey

All seven item means exceeded 4.20, reflecting that Human–AI collaboration was perceived as positive on all of the performance dimensions. Overall Agile project performance (M = 4.52, 88.9% agreement) was the most highly rated item.

Decision making quality (M = 4.40) and improvements in communication and transparency (M = 4.44) were also close behind. The lowest mean score (M = 4.22) was for the early risk identification, and even then, 77.8% agreed. It is important to note that the construct had high internal consistency (Cronbach α = 0.908) and an overall construct mean of 4.38 out of 5, which indicated that positive perceptions of collaboration were not only consistent, but reliable—meaning that they did not depend on a few extreme responses.

4.5 Challenges of AI implementation

As demonstrated in the previous sections, practitioners had generally positive perceptions of Human–AI collaboration, but it is also crucial to be aware of the barriers confronted. Five challenge statements were included in section 5 of the survey (Q12) and were rated by respondents. The findings are shown in Table 14.

Table 14. Descriptive Statistics: Challenges of AI Implementation

Challenge Items	Count(N)	Mean	SD	Agree %
AI tools sometimes produce inaccurate or misleading outputs	54	4.37	0.73	94.4%
Integrating AI tools into existing tools is difficult	54	4.24	0.75	81.5%
Data privacy or security concerns limit AI adoption	53	4.21	0.77	88.7%
Lack of trust in AI outputs is a major challenge	54	4.19	0.91	85.2%
Team faces resistance using AI tools	53	3.87	1.09	62.3%
Construct mean (Cronbach α = 0.782)	54	4.18	0.64	—

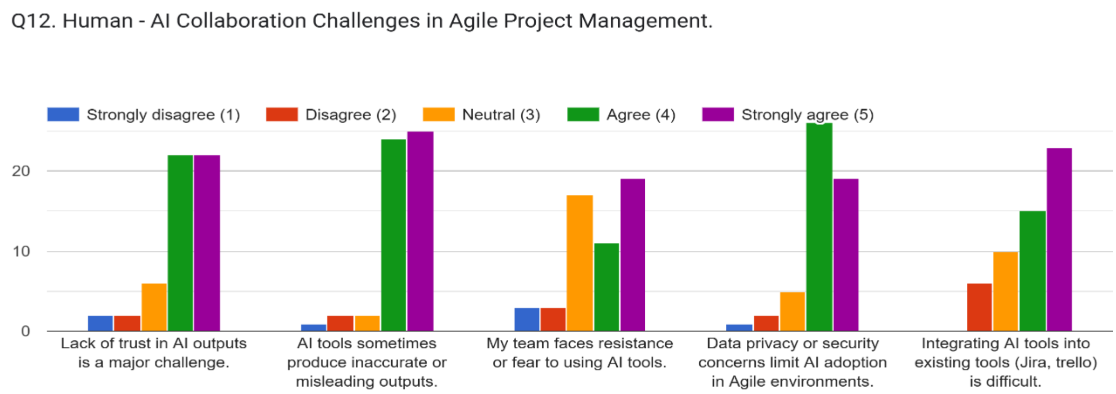

Figure 14. Bar chart from survey: Human-AI collaboration challenges

The most well-known challenge was that AI tools can generate inaccurate or misleading outputs (M = 4.37, 94.4% agreement), which had the highest agreement rate of all challenge items. Integration difficulty (M = 4.24) and data privacy and security (M = 4.21) were widely recognized as major barriers, closely related. Additionally, the lack of trust in AI outputs (M = 4.19, 85.2% agreement) confirms that accuracy and trust correlate as important issues for practitioners. Team resistance or fear (M = 3.87), on the other hand, was the least common with the widest range of scores (SD = 1.09). This suggests that while there is some resistance to the practice in many teams, it is not as widespread as the technical and epistemic resistance described above. The construct mean of 4.18 (Cronbach $\alpha = 0.782$) validates that practitioners recognize a significant and coherent set of risks related to AI use in Agile settings.

4.6 Strategies to overcome challenges

Q13 asked respondents to rate the level of their support for five specific strategies to overcome challenges related to AI. The results are given in Table 15.

Table 15. Descriptive Statistics: Strategies to Overcome Challenges

Strategy Items	Count(N)	Mean	SD	Agree %
Human oversight and final approval are required for AI-supported decisions	54	4.57	0.88	92.6%
Training and workshops help team members use AI tools effectively	54	4.56	0.60	94.4%
Strong data governance and privacy policies support safe AI use	54	4.54	0.66	90.7%
Regular team discussions about AI benefits and limitations reduce resistance	54	4.44	0.66	90.7%

Strategy Items	Count(N)	Mean	SD	Agree %
The team has clear processes for reviewing and validating AI outputs	54	4.41	0.79	90.7%
Construct mean (Cronbach α = 0.762)	54	4.50	0.52	—

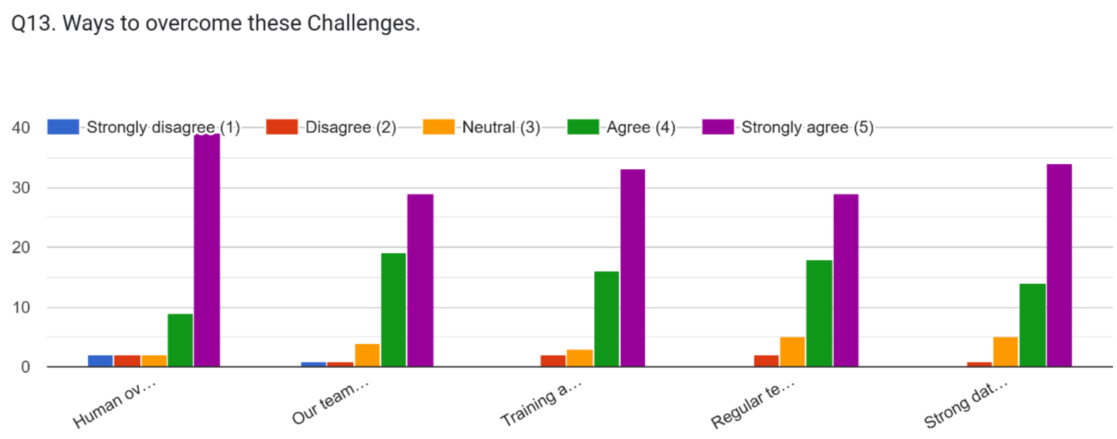

Figure 15. Bar chart from survey**:** Strategies to overcome AI challenges

The endorsement for all 5 of the strategy items was higher than any of the challenge items, with means between 4.41 to 4.57. Training and workshops (M = 4.56) and human oversight and final approval (M = 4.57) had the highest agreement rates of any strategy item in the entire survey, with 94.4% of respondents agreeing with these. Strong data governance and privacy policies (M = 4.54) were considered as equally important, which is directly in response to the privacy and trust issues identified above. Furthermore, more than 90% of the respondents approved of regular team discussion (M = 4.44) and clear validation processes (M = 4.41). Therefore, the strategy construct was found to have the highest mean of the four constructs, with Cronbach's α = 0.762. This discovery suggests not only that practitioners are aware of the risks of AI adoption but also hold clear and consistent opinions on how these risks should be mitigated in a human-centric manner (ForouzeshNejad et al., 2025; Mosqueira-Rey et al., 2023).

4.7 Reliability Analysis

Cronbach's alpha was used to test the internal consistency of all four main Likert-scale constructs. Table 16 presents the results.

Table 16. Reliability analysis results

Construct	Items	Cronbach α	Mean Score	Reliability
Human role (Q10)	5	0.894	4.70	Acceptable
Human–AI collaboration and performance (Q11)	7	0.919	4.38	Excellent
AI challenges (Q12)	5	0.821	4.18	Acceptable
Strategies to overcome challenges (Q13)	5	0.893	4.50	Acceptable

All Cronbach's alpha values were above the commonly accepted threshold of 0.70. The strongest reliability was found in the Human–AI collaboration/performance construct (α = 0.919). The human role construct also showed good reliability (α = 0.894). Both the challenges (α = 0.821) and the strategies to overcome challenges (α = 0.893) constructs demonstrated acceptable consistency. As a result, the measurement quality of all four constructs is confirmed, meaning that the items within each section measured related ideas in a consistent way.

4.8 Cross-Tabulation Analysis

To explore whether perceptions of Human–AI collaboration varied across practitioner groups, cross-tabulation analysis was performed by role and experience.

4.8.1 Cross-Tabulation by Role

Table 17. Mean collaboration/performance score by respondent role

Role	N	Mean	SD
Agile Coach	3	5.00	0.00
Product Owner	4	4.64	0.36
Scrum Master	14	4.52	0.55
Project Coordinator	8	4.50	0.56
Project Manager	13	4.29	0.59
Team member (Developer / Engineer)	8	4.18	0.69
Team Lead	3	4.10	1.01
Analyst	1	2.14	—

As shown in Table 17, Agile Coaches and Product Owners reported the highest mean performance scores (5.00 and 4.64, respectively), while Scrum Masters, the largest role group, also scored strongly (M = 4.52), as did Project Coordinators (M = 4.50). This pattern suggests that practitioners most directly involved in Agile facilitation and strategic decision-making are the most positive about the benefits of Human–AI collaboration. By contrast, Team Leads showed more variability (SD = 1.01), and the single Analyst respondent scored notably lower (M = 2.14), likely reflecting more limited direct experience with AI tools in an Agile context. However, because some groups are small, these cross-tabulation results should be treated with caution.

4.8.2 Cross-Tabulation by experience

Table 18. Mean project performance score by experience

Experience	N	Mean	SD
Less than 1 year	2	3.21	0.30
1–3 years	12	4.07	0.82
4–6 years	18	4.38	0.56
7–10 years	17	4.73	0.35
More than 10 years	5	4.40	0.84

The positive trend is very clear as experience goes from less than 1 year to the 7–10 year band. Those who have had experience with Agile for 7–10 years showed the highest mean score (M = 4.73, SD = 0.35) and the tightest distribution, which indicates their high and consistent level of confidence in the value of Human–AI collaboration. Those who had less than 1 year of Agile experience, however, achieved significantly lower scores (M = 3.21), indicating the need for additional practical experience to effectively use and assess Human–AI collaboration. This finding aligns with previous research that suggested that the effectiveness of utilizing the AI tool is enhanced by practitioner knowledge and contextual awareness (Hoda et al., 2023).

4.9 Correlation Analysis

Pearson correlation analysis was used to explore relationships among important constructs and AI engagement variables. All correlations are exploratory in nature and should be interpreted with caution because of the non-random sampling technique and the use of self-reported data. No causal inferences can be made. The complete results are shown in Table 19.

Table 19. Pearson Correlation Analysis

Variable 1	Variable 2	r	p-value	Strength
Overcoming strategy score (Q13)	Collaboration/performance (Q11)	0.748	< .001	Strong
Human role score (Q10)	Collaboration/performance (Q11)	0.718	< .001	Strong
Challenge score (Q12)	Collaboration/performance (Q11)	0.602	< .001	Moderate–Strong
AI purpose count (Q9)	Collaboration/performance (Q11)	0.467	< .001	Moderate
AI familiarity (Q6)	Collaboration/performance (Q11)	0.431	.001	Moderate
AI activity count (Q7)	Collaboration/performance (Q11)	0.400	.003	Moderate
AI tool count (Q8)	Collaboration/performance (Q11)	0.382	.004	Moderate
Challenge score (Q12)	Overcome strategy score (Q13)	0.507	< .001	Moderate

The most significant relationship found in the data set was the one between the overcoming strategy score and the collaboration/performance score ($r = 0.748$, $p < .001$). Put another way, the most highly favorable perceptions of Human–AI collaboration as beneficial to Agile performance were paired with the strongest endorsement of Human oversight, training, and validation processes, and Data governance. More closely related, the human role score had the second strongest correlation with performance ($r = 0.718$, $p < .001$), with those who most strongly believe in the importance of human judgment, leadership, and ethical oversight perceiving the greatest benefit from collaboration. The two findings allude to the same message that Human – AI collaboration should be based on human values and governance.

The challenge score was also moderately positively correlated with the performance score ($r = 0.602$, $p < .001$). But this correlation is difficult to interpret. It is not necessarily the case that difficulties translate into improved performance; instead, it is likely a reflection of the fact that practitioners who are most involved with AI tools are also most attuned to the potential benefits and risks of those tools. The engagement variables with AI had moderate positive correlation with perceived performance, with AI familiarity ($r = 0.431$), AI activity count ($r = 0.400$), and AI tool count ($r = 0.382$). Notably, intentional, goal-directed use of AI ($r = 0.467$) was the strongest of these, indicating that more than just using more AI tools, intentional, goal-directed use of AI was associated with perceived performance. Lastly, the strategy score is moderately correlated with the challenge score ($r = 0.507$), which is good: people who see the most challenges also support strong governance actions the most.

4.10 Summary of key findings

When examined as a whole, the findings across all sections of the survey point to a number of consistent and easily identified trends and themes that directly address the research questions of this thesis.

First, AI tools are already popular in the Agile lifecycle. Generative AI assistants (87.0%) and AI-powered project management platforms (83.3%) are the dominant tool types, and team communication (70.4%), sprint planning (68.5%), and backlog management (63.0%) are the most commonly AI-supported activities. Practitioners use AI primarily for routine speed-up (87.0%) and to enhance communication (79.6%), reinforcing the fact that AI is not a decision-maker, but an efficiency and productivity tool.

Second, and even more strikingly, the human role is seen as irreplaceable, even among those who are very active users of AI. The human role construct had the two highest item means in this entire survey (ethical decision M = 4.81; creative problem-solving M = 4.80), and 98.1% of the valid respondents agreed that “there is a need for human oversight in ethical and value-based decisions” and “in creative problem-solving.”

Third, Human–AI collaboration was widely seen as performance improving across all seven dimensions measured, including the highest mean (M = 4.52, 88.9% agreement) for the overall performance item. Furthermore, the cross-tabulation analysis shows that experienced practitioners and those who have a more facilitative role believe the greatest benefits in terms of performance are achieved through collaboration, indicating that experience and role centrality compound the benefits of collaboration.

Fourth, the problem of collaboration is appreciated, but the most recognized challenges are the accuracy of AI and the trustworthiness of data. The technical and epistemic risks (94.4% agreement) were much greater than team resistance (62.3%), suggesting that inaccurate or misleading AI outputs are a concern for practitioners more than cultural barriers are.

Fifth, most importantly for this thesis, endorsement of the human-centred governance strategies (r = 0.675) and the importance of human roles (r = 0.647) were the strongest predictors of perceived collaboration performance. Combined, these two findings constitute the main empirical finding of this study: Performance value of Human–AI collaboration in Agile is not only a function of the AI capabilities; it is maximised when there is a strong structure for human oversight, training, validation, and governance.

5 Discussion

This chapter presents the results of the study in relation to the research question, research objectives and literature. The central research question in this thesis was: How does Human and AI collaboration enhance the project performance in Agile project management? The findings indicate that while Human–AI collaboration can boost Agile project success, it is only when AI is viewed as a complementary tool and not a complete substitute for human skill. Each of the research objectives is addressed below, in turn, and the results are compared with previous studies, followed by an explanation of the findings based on the theoretical framework developed in Chapter 2.

5.1 AI Tool Use in Agile Project Management Activities

The findings reveal that AI has found its way into some Agile activities. The most popular areas to use AI are team communication (70.4%), sprint planning (68.5%), and backlog management (63.0%). This aligns with the literature which states AI can aid Agile teams in the automation of repetitive tasks, enhancement of estimation, facilitation of prioritisation and aiding teams in handling vast amounts of project data (Almalki, 2025; ForouzeshNejad et al., 2025; Hoda et al., 2023).

The most common types of tools utilized were generative AI assistants and AI-powered project management platforms, with 87.0% and 83.3% respectively. These tools are especially appropriate in Agile environments where teams are handling numerous tasks, priorities change often and there is an ongoing need for communication. AI can save hours of practitioner time on manual tasks such as summarising meeting transcripts and preparing sprint reports, analysing backlog items and even aiding capacity planning, all tasks that don't directly contribute to project value.

But the results don't indicate that the Agile team will be replaced by AI. AI is mainly used in the practice to streamline mundane tasks and enhance communication, rather than to inform strategic decisions about a project. While automated backlog prioritisation tools are the most autonomous and judgment-oriented AI capability available, only 13.0% of respondents were using them, making it the lowest adopted tool type available. This selective pattern aligns with Hoda et al.'s (2023) idea of augmented agile, in which AI can help Agile teams, but human values and judgment are paramount. The data reveal that AI is best used in tandem with rather than in place of the team.

5.2 The Continued Importance of Human Roles

The most positive result from this research is that there was almost universal agreement that the human factor is a major part of Agile project management. The highest rated items of the entire survey were ethical and value-based decision-making (M = 4.81, > 96% agreement), leadership and team motivation (M = 4.81, > 96% agreement), and creative problem-solving (M = 4.80, > 96% agreement). This belief has a construct mean of 4.70 (α = 0.803), meaning it is very strong and internally consistent throughout the sample.

This result is a good indication of the human-centred nature of Agile. The Agile Manifesto clearly states the importance of individuals and interactions, customer collaboration, and responding to change over processes and tools (Beck et al., 2001). Many of the core principles of agile methods—such as self-organizing teams, psychological safety, negotiation, and continuous learning—are missing from the realm of AI (Dong et al., 2024). While AI can analyse historical data and recommend which backlog item to prioritize, it is essential for the Product Owner to consider other factors such as customer value, business impact, stakeholder relationships, and ethical considerations, which cannot be solely data-driven.

Notably, this belief was shared by all demographic segments, including those who had the strongest AI familiarity and most extensive use of AI tools. Even those who use AI the most do not lower their opinion of the irreplaceable role of humans. This indicates that

AI tools do not make practitioners less aware of what AI does not do, with practical implications for how AI is communicated to Agile teams within their organizations.

5.3 Human–AI Collaboration and Agile Project Performance

The findings indicate that there is a positive relationship between Human – AI collaboration and Agile project performance in all the seven dimensions assessed. The highest scores were given for overall performance (M = 4.52, 88.9% agreement), communication and transparency (M = 4.44) and quality of decision making (M = 4.40). The lowest mean score (M = 4.22) but still with 77.8% agreement was for early risk identification. This construct has a Cronbach's alpha of 0.908, so these perceptions are coherent and reliable in the sample.

This aligns with previous research indicating that AI can enhance Agile project forecasting, risk identification, resource allocation, and decision support (Almalki, 2025; Chapal Barua et al., 2025; ForouzeshNejad et al., 2025). The relatively lower score for risk identification may be because AI-driven risk prediction needs high data quality and integration, which not all Agile teams currently have, not because of any inherent limitations of agile collaboration.

This finding is complemented by the correlation analysis. Interestingly, endorsement of human-centred governance strategies was the strongest predictor of perceived collaboration performance ($r = 0.748$, $p < .001$) and belief in human roles ($r = 0.718$, $p < .001$), with the number of AI tools used ($r = 0.382$) and the range of AI-supported activities ($r = 0.400$) following in rank. This is the main empirical finding of this thesis: It is not the extent of AI adoption that matters for Agile performance, but the quality of human structures that envelop the adoption. But as one respondent's data indicates, AI performance value is not derived from AI tools alone, but from responsible, governed, human-led use of AI.

5.4 Challenges of AI Implementation in Agile Project Management

The study has identified a clear and coherent set of challenges concerning the implementation of AI. The most well-known was the inaccuracy or misleadingness of the AI outputs (M = 4.37, 94.4% agreement). This is particularly important in Agile development, where teams regularly make decisions during sprint planning, daily standups, and sprint reviews and retrospectives. Wrong AI recommendations, underestimates or overestimates, or incorrect summaries can be multiplied throughout the sprint and lower the quality of decision-making.

This result is in line with the explainability and human oversight literature. Forouzesh-Nejad et al. (2025) state that AI predictions in Agile projects need to be explainable to understand and evaluate the reasoning behind a recommendation. Cinkusz et al. (2024) also report that LLMs can be useful to assist with Agile work, but need to be reviewed by humans, especially in open-ended and ambiguous project situations or when dealing with ethical issues. The current data does show that this is a limitation practitioners feel firsthand and is the leading practical challenge to confidently using AI.

The next-most recognised challenges were data privacy and security issues (M = 4.21, 88.7%) and integration complexity (M = 4.24, 81.5%). There are many types of data in Agile projects that are sensitive to privacy, such as task history, team performance data, customer requirements, and internal communications. Organisations that do not have a solid data governance policy are at risk of legal liability under data protection laws like GDPR and may also experience a lack of trust in AI systems, even when they are technically capable of using them.

The least recognised challenge was team resistance (M = 3.87, 62.3%) and was also the most variable (SD = 1.09). It's a significant contrast to other literature that views cultural resistance as a major factor affecting adoption (Hamza et al., 2025; Mogbojuri et al., 2025). In fact, for the experienced and AI-literate practitioners in this sample, they do not seem to be so worried about people's willingness to embrace AI but about whether the AI outputs will be accurate, transparent, and privacy-safe. This challenge is not so much cultural as technical and epistemic, with direct implications for where organisations should focus their efforts when it comes to barriers to AI adoption.

5.5 Strategies to Improve Human–AI Collaboration

There was strong and consistent support by the respondents for all five governance strategies presented. The highest endorsement of all items across the entire survey (even higher than performance benefits) came for human oversight and final approval (M = 4.57, 92.6%) and training and workshops (M = 4.56, 94.4%), suggesting that practitioners have clear views not only on the value of collaboration, but also on the conditions required to make it work responsibly.

This high level of acceptance of human oversight fully relates to the Human-in-the-Loop (HITL) governance framework, where AI is used as a decision support tool but not a decision authority (Mosqueira-Rey et al., 2023). This is particularly relevant to Agile project management: decisions are made on a regular basis with imperfect information, changing priorities of the stakeholders involved, and with a subjective judgment that is difficult for algorithms to duplicate. Practitioner data indicate that HITL is not only an ideal theoretical approach, but also a practice expectation being actively promoted.

The support of training and workshops was also good. This is related to TAM (Technology Acceptance Model) which suggests that individuals are more likely to adopt a technology if they find it useful and easy to use (Davis, 1989). By understanding the strengths and limitations of AI tools and the ability to critically assess their results, Agile team members can make more informed and confident use of them, while also avoiding inaccuracies that could lead to wrong decisions for the project. In this reading, training is not about being a nice thing to do, it is a governance mechanism which directly influences how useful AI collaboration is perceived to be.

There was also broad support for strong data governance and privacy policies (M = 4.54, 90.7%), which directly address concerns about privacy and trust raised in Section 5.4. The mean for the strategy construct was the highest of all four constructs (4.50, α = 0.762), and the moderate correlation between challenge recognition and strategy endorsement (r = 0.507) indicates that those who recognize the risks most clearly are also most willing to implement them systematically and constructively.

5.6 Experience and Role as Moderating Factors

Analysis of the cross-tabulation data shows that the nature of practitioners' experience and role influences their perception of the value of Human-AI collaboration. The highest mean (M = 4.73, SD = 0.35) and least distribution for collaboration performance was reported by practitioners with 7-10 years of Agile experience, showing high and consistent confidence level. Persons with less than one year of experience had a significantly lower score (M = 3.21), and a larger standard deviation.

This experience gradient is of real-life significance. It proposes that the benefits of Human-AI collaboration are not equally accessible to all practitioners but to some extent rely on the tacit knowledge and contextual judgment that Agile experience enables. However, a practitioner who has experience in sprint cycles, retrospectives and stakeholder management can critically assess an AI velocity forecast – they can tell what is plausible or not. A practitioner with six months experience may not have this reference point and will be less able to utilize the AI output productively or identify when the AI output is incorrect and before it translates into a decision. Organisations that don't invest in practitioner development in conjunction with the introduction of AI tools may therefore not gain as much from the collaboration benefits of the data as a whole might indicate.

With respect to the role dimension, Agile Coaches and Product Owners rated highest in terms of the mean of their collaboration performance, and the team leads had the highest standard deviation (SD = 1.01). The roles most deeply involved in Agile planning and facilitation, who engage with the insights provided by AI on a regular basis across sprint ceremonies, stand best to reap the rewards of AI-generated insights. This discovery corroborates the overall claim that the value that the AI layer provides is defined by human governance systems and the humans who have mastered them.

5.7 Discussion in Relation to the Theoretical Framework

The results of this study can be reasonably interpreted in relation to the three theories outlined in Chapter 2: Knowledge Management Theory, Socio-Technical Systems Theory, and the Technology Acceptance Model. Finally, these theories will not be used as standalone explanations of each individual finding, but rather as ways to interpret findings from the data, and a specific theory will be supported, refuted or modified by the data in the location where the data most directly demonstrates this.

5.7.1 Knowledge Management Theory

Nonaka and Takeuchi (1995) distinguished between the two types of knowledge: explicit knowledge, which is structured, documentable, and can be transferred, and tacit knowledge, which is integrated in the experience, judgment, and interpersonal context. The results of this study dovetail nicely with this distinction. In this sample, AI tools are applied massively to explicit knowledge activities: Creating sprint reports, analyzing velocity data, summarizing meeting transcripts, and identifying risk indicators from structured data. In fact, these are the sort of things that Knowledge Management Theory says AI can do quite well, since they are codifiable, processable information.

The tacit knowledge domain, on the other hand, is the one that has the most empirical support where the human role plays. Those tasks most reliant on accumulated experience, contextual judgment, and relationship intelligence — all rated irreplaceably human — are ethical/value-based decision making (M = 4.81), leadership (M = 4.81), and creative problem-solving (M = 4.80). Tacit knowledge is the most important and least replicable organizational resource and is the one that cannot be automated, as described by Grant (1996). This near-unanimity among respondents is a testament to this: even those who apply AI to numerous Agile tasks are clear on the activities where tacit knowledge is essential. This interpretation is further supported by the experience effect in the cross-tabulation (7–10 year group, M = 4.73): The more practitioners have developed tacit knowledge, the more they feel that the value of AI collaboration is in being able to contextualize and critically assess what AI provides.

5.7.2 Socio-Technical Systems Theory

According to Socio-Technical Systems Theory (Trist & Bamforth, 1951), the successful performance of an organization depends on optimizing both the social subsystem (individuals, teams, culture, and practices) and the technical subsystem (tools, systems, and processes). It is the convergence of these subsystems that gets optimal results, and not either subsystem alone. This thesis provides ample empirical evidence of this prediction.

The technical subsystem of this work consists of AI tools: generative AI, NLP pipelines, predictive analytics, and AI-integrated project management platforms. The social subsystem consists of practitioners of Agile and the social practices they engage in – sprint facilitation, stakeholder negotiation, ethical monitoring, retrospective learning, and team leadership. As illustrated by the survey data, when both these subsystems operate together, with AI processing data volume and speed, and humans exercising contextual authority and governance, practitioners see a wide range of their business perform better across operational, relational, and strategic parameters.

The central empirical finding of this thesis – that governance strategy endorsement (r = 0.748) and human role valuation (r = 0.718) are the strongest predictors of perceived collaboration performance, well ahead of the number of AI tools (r = 0.382) – is the socio-technical argument made quantitative. It validates the fact that technical ability is not enough to achieve effective collaboration, without a social and governance framework that goes along with it. We do not believe that the most successful players in Human–AI collaboration are the ones that have implemented the most AI tools in Agile, but the ones who have established the social mechanisms to make AI power play through human judgment, such as training programs, validation procedures, oversight processes, and data governance policies.

5.7.3 Technology Acceptance Model

The Technology Acceptance Model (Davis, 1989) is a theory that suggests that the adoption of a technology depends on two perceptions: perceived ease of use and perceived usefulness. If both are high, then acceptance occurs, if either is uncertain, or low, adoption is limited, even if technically capable.

Adoption process in this study is in close proximity to the TAM predictions. Generative AI assistants (87.0%) and AI-integrated project management platforms (83.3%) are widely accepted as they can be seen as useful — tasks get done faster, communication improves, and reports are produced with less effort. Only 13.0% of respondents use automated backlog prioritisation tools, however. These tools exist but there is not yet a strong perceived value of the tools for an Agile function with significant judgment needs or high strategical sensitivity, and perceived risk for error is high. TAM is a prediction of just such a selective boundary.

TAM also accounts for the experience gradient that is found in the cross-tabulation. The more useful the feature, the more competent the practitioner will be: a practitioner with 8 years' Agile experience can assess an AI-generated forecast, and make decisions as to when to follow it and when to ignore it. This is a crucial skill that gives AI-generated content value and not just uncertainty. If a practitioner has only six months of experience, then they do not have such evaluative experience and thus, see AI collaboration as less reliably beneficial. The very high percent (94.4%) for the strong endorsement of training and workshops as a governance strategy is consistent with TAM in this regard: training is a means for building perceived usefulness throughout the team.

5.8 Conceptual Framework for Human–AI Collaboration

Based on the empirical results and the three theoretical models that are used in Section 5.7, a conceptual model for effective Human–AI collaboration in Agile project management is proposed. The framework illustrates four layers that are interconnected, and the data consistently point towards socio-technical architecture.

Layer 1: AI Support Layer (Technical Subsystem). AI tools such as Generative AI, NLP, ML models, and AI agents offer task-level assistance throughout the Agile lifecycle, from backlog refinement to sprint velocity prediction, automated meeting summaries, real-time risk flagging, and even stakeholders' communication support. This layer adds speed, volume, and consistency of data analysis that the human layer just can't bring at scale. It refers to explicit knowledge tasks, which Knowledge Management Theory describes.

Layer 2: Human Role Layer (Social Subsystem). Practitioners are irreplaceable and provide judgment, leadership, creativity, and ethical oversight. Product Owners set strategic product vision. Scrum Masters are reading the team dynamics and making psychological safety happen. Creativity and problem-solving with domain knowledge are applied by the developers. Tacit knowledge is the source from which all other knowledge and values derive; it's the contextual, relational, and experiential intelligence that cannot be encoded or automated. The human layer determines the context for AI recommendations, their suitability, and subsequent actions.

Layer 3: Governance and Trust Layer (Joint Optimisation Mechanism). This is the link between the two layers above and the most important factor of how well collaboration works (r = 0.748). It includes human oversight and approval procedures, training and AI literacy initiatives, data governance and privacy protocols, as well as regular validation of AI-generated content and team conversations about the limitations of AI. This joint optimisation layer, in Socio-Technical Systems Theory parlance, is the structured social practices that are necessary for the technical subsystem to serve, and not supplant, the social subsystem. From a TAM perspective, it's the layer where perceived usefulness is developed and sustained throughout the team over time.

Strategies / Performance Outcomes — Agile Layer 4. There is a clear positive correlation between the three layers above and practitioners' performance by many measures – delivery reliability, sprint predictability, decision quality, risk handling, team effectiveness, and stakeholder value delivery. The framework also suggests that the benefits of improved performance are more related to the quality of the governance layer, rather than the number of AI tools used, which is directly supported by the correlation data, and aligned with Socio-Technical Systems Theory.

This framework builds on previous research by Hoda et al. (2023) about Augmented Agile and Dam et al. (2019) about AI-powered Agile project management by adding empirical practitioner data to the governance layer and clearly stating the theoretical basis of the framework. It offers a model that organisations can apply to review their current approach to AI integration and gauge potential areas where governance processes may not be as advanced as the technical capabilities.

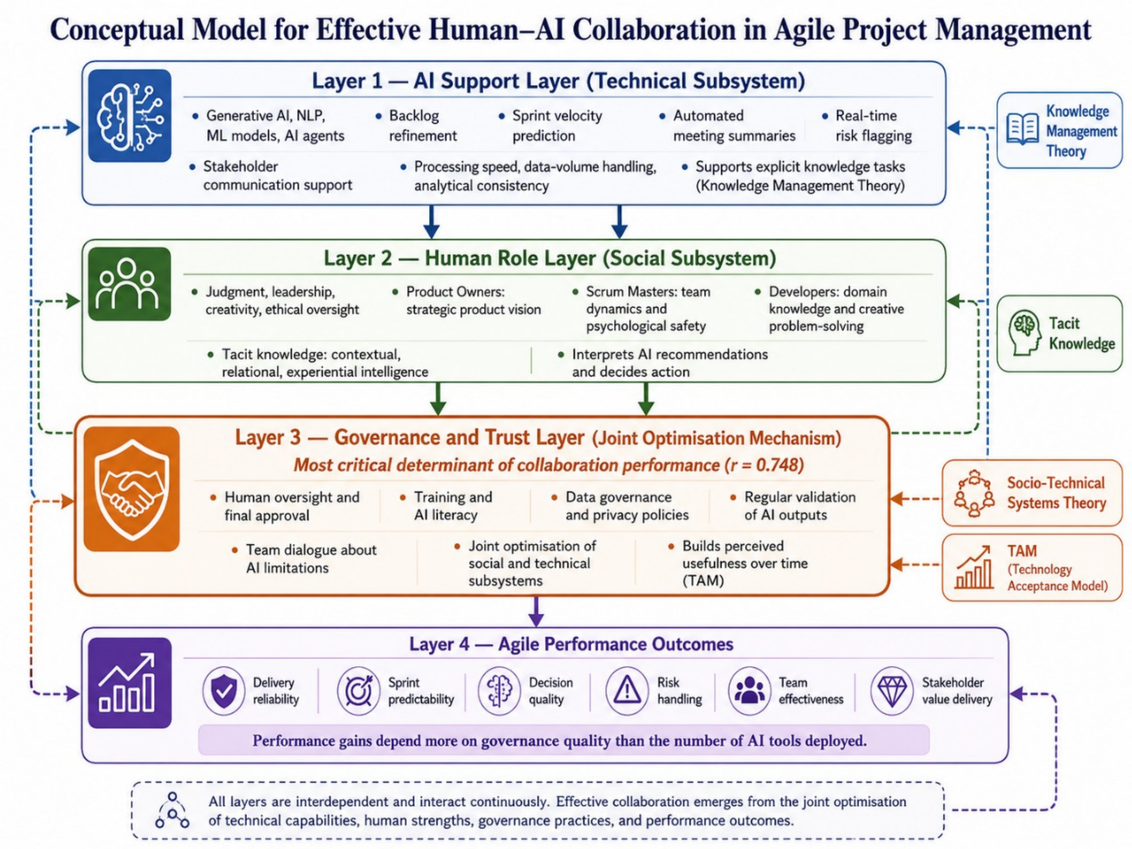

Figure 16. Conceptual Framework (Human–AI Collaboration in Agile Project Management)

5.9 Overall Interpretation

Overall, the results show that Human–AI collaboration improves Agile project performance in three main ways. The first is efficiency: AI can help with routine aspects of software development like reporting, communication, backlog analysis, and sprint planning. Second, AI enhances decision support by assisting teams to spot threats, process project data, and analyse information at a speed and scale that humans alone can't sustain. Third, human decisions are enhanced by the use of AI by applying judgment, ethics, creativity, and contextual understanding, which AI can't do.

The main contribution of this thesis is that balanced and governed collaboration is a way to enhance Agile performance. The added value of AI should be speed, analysis, automation, and prediction. Humans should take their place as meaningful givers of responsibility, leadership, and final decision-making power. What is crucial for the investment organisations to make between these two is a governance layer that connects and mediates between them.

In the future, Agile project management will be neither entirely human-driven nor entirely AI-driven. It's a fusion, to be precise, a hybrid approach, where you have human and AI teaming up, and humans being in command. It goes naturally along with the Agile way of thinking, which already promotes adapting, learning, feedback and problem solving together. Properly managed, AI accentuates and complements these values.

6 Conclusion

The final chapter summarizes the assessment of how well the research goals were met and comments on the theoretical and practical implications of the research. It also includes some discussion on the limits of the research and suggests some areas where additional research may proceed. The chapter concludes with a few remarks to place the study in the larger context of the future of Agile project management in the AI era.

6.1 Answers to Research Questions

The main research question in this thesis was: How does human and Artificial Intelligence collaboration enhance agile project management performance? The results clearly answer the question from an empirical perspective. By combining the best of both worlds, human–AI collaboration unlocks Agile project performance by leveraging AI's speed and scale in data processing, particularly in reporting, sprint planning, risk pattern recognition, and communication facilitation, while still preserving the essential human qualities needed for Agile: contextual understanding, ethical considerations, creativity, and leadership. It's not just a sum of the parts; the performance increase will come from the effectiveness of the governance framework that shapes how the AI's output is verified, understood, and applied by the practitioners.

Each of the five research objectives is discussed in turn below.

Objective 1 – Identify Agile activities where AI tools are currently being used: AI is being used the most in team communication, sprint planning, and backlog management, while meeting summarization and analytics dashboards are also popular. Slightly more autonomous tools like automated backlog prioritisation are still in their infancy, with practitioners being wary of tools that have a certain degree of judgment involved.

Objective 2: Identify the role of humans in decision-making, leadership, and collaboration: The human practitioner is considered essential in all five of the objectives tested: ethical decision-making, leadership and motivation, contextual understanding, stakeholder negotiation, and creative problem solving. This result is consistent regardless of the role or the level of AI familiarity, suggesting that the use of AI does not reduce practitioners' recognition of the value of the irreplaceable human component in Agile.

Objective 3—Determine the impact of Human–AI collaboration on Agile project performance: Collaboration is perceived as beneficial in all seven dimensions, with the highest perceived improvement in overall project performance, the quality of communication, and decision-making. Experienced practitioners and individuals in facilitative roles report that the potential benefits are most pronounced, reflecting how tacit knowledge and a pivotal role in the organization can intensify the impact of AI-driven insights.

Objective 4—Identify challenges and strategies to overcome: AI output inaccuracy, integration complexity, and data privacy are the most significant challenges. Concurrently, respondents strongly agree that human supervision, formal training, data management, and validation procedures as elements that can enable these risks to be managed responsibly.

Objective 5 – Develop a conceptual framework: The four-layer conceptual framework presented in Chapter 5 brings together the empirical results and all three theoretical frameworks and can serve as a tool for organisations to assess and enhance their approach to Human – AI integration in Agile settings.

6.2 Theoretical Contributions

This thesis is a small but specific contribution to three theory areas, used in the context of Agile project management with the help of AI.

The study provides evidence at the practitioner level that AI tools are successful at explicit knowledge tasks, while other tasks (e.g., ethical reasoning, leadership, and creative problem solving) are still in the human realm, consistent with Knowledge Management Theory (Nonaka & Takeuchi, 1995). In line with Socio-Technical Systems Theory (Trist & Bamforth, 1951), the correlation data reveal that the governance structure is a better predictor of perceived performance than the extent of AI tool use, with the joint optimisation principle being supported in a knowledge-intensive project context. Lastly, the experience gradient observed in the cross-tabulation analysis implies that the usefulness of AI in Agile work is a dependent variable, and training is a mediator variable, not only assisting practitioners in adopting AI but also serving as a governance mechanism itself.

6.3 Practical Implications

The results of this study have several implications for Agile practitioners, team leaders, and organisations that are interested in or investing in AI-assisted project management.

The study shows that AI tools should be considered as augmenting, not automating, Agile teams and practitioners. Practitioners need to use AI for what it is best at: handling vast amounts of structured data, creating sprint summaries, identifying risk trends, and standardising reporting—and, of course, stay the expert in strategy, ethics, building stakeholder relationships, and fostering team culture. The strong consensus around the critical role of human oversight in effective collaboration (92.6%) suggests that teams should not consider validating AI-generated content as a governance exercise but rather as an integral part of their work.

The data experience gradient indicates a mentorship opportunity for team leaders and Scrum Masters. In the realm of ChatGPT contextualization, seasoned practitioners clearly outperform their less experienced peers in terms of leveraging and benefiting from AI insights. AI output evaluation should be explicitly taught to newer team members as a critical AI literacy skill, as part of onboarding and continuous learning by agile coaches and senior agile practitioners.

The correlation data show that investments in governance infrastructure give higher return on investment for organisations and project management offices than investments in more AI tools. In particular, organisations should focus on establishing clear data governance and privacy policies, providing structured training programs that highlight the benefits and risks of AI tools, defining validation and human decision-making processes for AI-driven decisions, and facilitating regular discussions about the use of AI within the team, which helps identify the concerns and foster understanding. These measures tackle the most frequently mentioned pain points (AI output inaccuracy, data privacy, and integration difficulty) and directly support the governance conditions most strongly correlated with performance outcomes, as revealed by the correlation analysis.

Lastly, for tool developers and vendors, the low use of automated backlog prioritisation tools (13.0%) when compared to the use of other AI features indicates that the market is not yet convinced that AI can consistently make decisions related to strategic judgment in Agile planning. AI providers in Agile should focus on making their tools explainable, so that Agile practitioners can verify and optionally reject AI suggestions and don't have a tool as the ultimate decision-maker.

6.4 Limitations of the Study

This study has a number of limitations that need to be considered when interpreting the findings and evaluating their generalisability.

Firstly, the sample was selected using non-probability convenience sampling using professional networks and online Agile communities. The 54 respondents represent a non-statistically representative sample of the global population of Agile practitioners. There may have been a self-selection bias, as individuals already interested in AI were more inclined to participate, which could have skewed the data towards positive perceptions of AI collaboration.

Second, all data are perceptual and self-reported. The respondents evaluated the impact on the end result of the Human-AI collaboration on their own experience and opinions. Respondents might have been subject to social desirability bias, leading them to report more positive perceptions of AI than they would necessarily have experienced.

Thirdly, this is a cross-sectional study that provides a snapshot of perceptions at one point in time. Due to the fast evolution of AI and its usage, the results can change rapidly. Future perceptions and practices would likely evolve with the maturation of AI capabilities and the growing experience of practitioners, which would be captured by a longitudinal design.

Fourth, although the sample includes a cross-section of industries and countries, the sample is largely from the software and technology sectors – the main domain where Agile is practiced – and so the findings might not be applicable to sectors where Agile is less established, for example, healthcare project management, manufacturing, or public administration.

Fifth, the researchers did not collect objective performance indicators, like sprint velocity or delivery predictability scores, or defect rates. The use of perceived performance indicates that the study reflects perceptions of the outcomes of the collaboration and not actual, verifiable project outcomes. Further work needs to try to validate practitioner perceptions with objective performance measures.

6.5 Directions for Future Research

Future research could benefit from the following avenues explored by this study.

Larger and more representative samples: This study had a convenience sample of 54 respondents, which is not statistically generalizable. Future research should seek larger and probability-sampled samples that include more industries, countries and organisational sizes. Thus, more complex analysis methods like structural equation modelling or confirmatory factor analysis could be used to test the causal relationship that was assumed in the conceptual framework presented in this thesis, such as whether governance maturity mediates between the use of AI tools and project performance.

Longitudinal research designs: This study is cross-sectional, representing perceptions at one point in time, in a field that is rapidly evolving. A longitudinal design that would follow the same teams or practitioners across several sprint cycles, or indeed years, would allow us to see how attitudes to working with AI change as practitioners become more experienced, how team performance changes as governance practices change, and whether there is a fading of scepticism towards AI outputs when it becomes more reliable and explainable.

Mixed-methods approaches: The survey data is not enough to fully represent the realities of Human–AI collaboration in practice. Future research efforts could be based on quantitative surveys, with qualitative research techniques like in-depth interviews, focus groups or ethnographic observation of actual Agile ceremonies. This would reveal how practitioners actually balance out AI suggestions and their own understanding at sprint planning or backlog refinement meetings, and what governance structures are intuitive and which are cumbersome in day-to-day Agile practices.

Objective performance measurement: The data for this study were all self-reported, perceptual. There is a need for further studies to try to validate practitioner perceptions with objective project measures before and after AI tools were introduced, such as trends in sprint velocity or defect rates, or scores of stakeholder satisfaction. This would change perceived performance to demonstrated performance and would assist organisations in making more evidence-based investment decisions.

The advent of Agentic AI: Possibly most importantly, a key area for further research is Agentic AI systems, which are systems that can plan, execute, and adapt across multi-step tasks without significant human input. These governance principles, as identified in this thesis, may require a major overhaul as these systems start to perform a range of functions such as backlog management, sprint scheduling, and even stakeholder communication. As AI transitions from action suggestions to execution, research will be required to explore the nature of human oversight for Agile teams and the kinds of new structures for Human–AI collaboration that are appropriate in that context.

6.6 Concluding Remarks

In 2001, the authors of the Agile Manifesto put individuals and interactions over processes and tools (Beck et al., 2001). This thesis proposes that the principle has not been undermined by the advent of AI; it has been amplified. Despite the wide use of AI tools and techniques, there continues to be a strong emphasis on human judgment, ethical reasoning, and leadership. Although AI has substantially accelerated Agile teams and improved their information, its essence remains the same: people making good decisions together.

This is a very straightforward thesis. However, human–AI collaboration is effective not when organisations have the highest number of AI tools, but when they have the human frameworks in place: oversight, training, validation, and trust – to have AI serve the team, rather than lead it. That is the true place of performance gains: a balance that is governed, manned.

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Appendices

Appendix 1. Survey questionnaire

Section 1 of 6

Survey for Master's thesis

Dear Participant,

My name is Shafiul Alam. I am a master's student at the University of Vaasa,Finland. I kindly invite you to participate in this anonymous survey for academic research purposes.

Thesis title: Human and Artificial Intelligence Collaboration to Enhance Agile Project Management Performance.

Purpose: This survey explores how human expertise and Artificial Intelligence (AI) tools work together in Agile project management and how this collaboration improves project performance.

Time required: Approximately 8–10 minutes.
Confidentiality: All responses are completely anonymous. No personal or company names are collected.
Data use: Responses will be used only for this thesis and stored securely in accordance with GDPR.

There are no right or wrong answers — please answer based on your real experience. By clicking next, you are confirming that you are:

- Have experience in Agile Project management
- Understand the information above, and voluntarily agree to participate in this research.

Thank you for taking part in this master's thesis survey.

If you have questions, please contact: Shafiul Alam (x0497487@student.uwasa.fi).

SECTION 1 — Respondent Profile

These questions help us understand who our respondents are. No identifying information is collected.

Q1. What is your current primary role in Agile project management? *

- ◯ Product Owner
- ◯ Project Manager
- ◯ Project Coordinator
- ◯ Scrum Master
- ◯ Agile Coach
- ◯ Analyst
- ◯ Team Lead
- ◯ Team member (Developer / Engineer / Tester)
- ◯ Other: ______

Q2. How many years of experience do you have working in Agile Project Management? *

- ◯ Less than 1 year
- ◯ 1–3 years
- ◯ 4–6 years
- ◯ 7–10 years
- ◯ More than 10 years

Q3. In which industry do you mainly work? *

- ◯ Software / Technology / IT
- ◯ Engineering / Manufacturing Industry
- ◯ Construction
- ◯ Education / Research
- ◯ Other: ______

Q4. What is the approximate size of your current Agile team? *

- ◯ Fewer than 5 people
- ◯ 6–10 people
- ◯ 11–15 people
- ◯ 16 - 20 people
- ◯ More than 20 people

Q5. In which country is your team mainly located?

Your answer

Q6. How familiar are you with AI tools in general? *

- ◯ Not familiar at all
- ◯ Slightly familiar
- ◯ Moderately familiar
- ◯ Very familiar
- ◯ Expert level

SECTION 2 - Use of AI tools in Agile Project Management

For this survey, 'AI tools' include any tools using machine learning, predictive analytics, natural language processing, or generative AI (eg, ChatGPT/Copilot, AI features in Jira, Asana, etc.).

Q7. In which Agile project management activities do you or your team use AI tools?
Please select all Agile project management activities where you use AI-supported tools. This may include tools used for suggestions, summaries, estimation, prioritization, risk alerts, reporting, or automated support during project work.

- ☐ Backlog Management
- ☐ Sprint Planning
- ☐ Daily Stand-up (summarisation or action tracking)
- ☐ Team Communication
- ☐ Sprint Retrospective and continuous development (eg, analyzing feedback, identifying patterns)
- ☐ Risk Identification and Monitoring
- ☐ Stakeholder Communication (eg, preparing demos, summaries, documentation and reporting)
- ☐ Decision support tasks
- ☐ None of the above
- ☐ Other: ________

Q8. Which of the following AI tools or features have you used in Agile project management? (Tick all that apply)

- ☐ Generative AI assistants (eg, ChatGPT, Claude, Gemini, etc.)
- ☐ AI-powered project management platforms (eg, Jira, clickup)
- ☐ AI Agents for tasks Automation (create product backlog, backlog prioritization, Sprint planning, resource allocation, etc.)
- ☐ AI-driven risk or dependency detection tools (machine learning)
- ☐ Meeting summarisation/transcription tools (Zoom, Google Meet, etc.)
- ☐ Reports/dashboards with AI analytics
- ☐ I am not sure which tools qualify as AI-powered
- ☐ Other: ________

Q9. What is the main purpose of using AI in your Agile Project Management? (Tick all that apply)

- ☐ Speed up routine tasks
- ☐ Improve idea generation, estimation and planning
- ☐ Improve decision-making
- ☐ Identify risks early
- ☐ Improve communication
- ☐ Generate reports or summaries
- ☐ Improve team productivity
- ☐ Other: ________

SECTION 3 - Human role in Agile Project Management along with AI

These questions explore how human judgment, oversight, and trust operate alongside AI tools.

Please indicate your level of agreement with the following statements.

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Q10 To what extent do you agree with the following statements about the role of humans is essential in Agile project management?

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
Human judgment is essential even when AI provides recommendations.	○	○	○	○	○
Leadership and team motivation remain primarily a human responsibility.	○	○	○	○	○
Contextual understanding and stakeholder negotiation still require strong human involvement.	○	○	○	○	○
Creative problem-solving in uncertain situations depends on human expertise.	○	○	○	○	○
Ethical and value-based decisions require human oversight.	○	○	○	○	○

SECTION 4 - Human–AI collaboration to enhance Agile project management performance

Please rate your level of agreement with each statement. Base your answers on your experience.

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Q11. To what extent do you agree that human–AI collaboration improves Agile project management performance in following area?

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
Human–AI collaboration improves product backlog refinement and prioritisation.	○	○	○	○	○
AI insights help human sprints planning and delivery predictability accurately.	○	○	○	○	○
AI helps identify the project risks earlier.	○	○	○	○	○
Human judgment combined with AI recommendations improves project decision-making.	○	○	○	○	○
AI tools help the team allocate tasks and resources more effectively.	○	○	○	○	○
Human–AI collaboration improves communication and transparency within the Agile team.	○	○	○	○	○
Human–AI collaboration enhance overall Agile project performance.	○	○	○	○	○

SECTION 5 - Challenges of AI Implementation in Agile project management and way to overcome them

What barriers or concerns have you encountered in human–AI collaboration? and ways to solve the problem.

Please indicate your level of agreement with the following statements.

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Q12. Human - AI Collaboration Challenges in Agile Project Management.

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Lack of trust in AI outputs is a major challenge.	○	○	○	○	○
AI tools sometimes produce inaccurate or misleading outputs.	○	○	○	○	○
My team faces resistance or fear to using AI tools.	○	○	○	○	○
Data privacy or security concerns limit AI adoption in Agile environments.	○	○	○	○	○
Integrating AI tools into existing tools (Jira, trello) is difficult.	○	○	○	○	○

Q13. Ways to overcome these Challenges.

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Human oversight and final approval are required for important AI-supported decisions.	○	○	○	○	○
Our team has clear processes for reviewing and validating AI outputs before using them.	○	○	○	○	○
Training and workshops help team members using AI tools with exiting tools.	○	○	○	○	○
Regular team discussions about AI benefits and limitations reduce resistance.	○	○	○	○	○
Strong data governance and privacy policies support safe AI use.	○	○	○	○	○

Takaisin

Lähetä

Tyhjennä lomake

Appendix 2. Python Statistical Analysis Code

All the statistical analyses presented in Chapter 4 were performed using the following Python script. Python 3 and the pandas (data manipulation), scipy (Pearson correlation), numpy (numerical calculations), and pingouin (Cronbach's alpha with confidence intervals) libraries were used to run the script. The full script is given for the complete reproduction of all results.

https://drive.google.com/file/d/196W8gNdtQsg6JFGwWlH8OvfGLqbxtkJ9/view?usp=drive_link

```python

import pandas as pd
import numpy as np
from scipy import stats
import pingouin as pg
import re
import warnings
warnings.filterwarnings('ignore')

# ── CONFIG ──────────────────────────────────────────────────────
DATA_PATH = "/content/shafiul/Survey for Master thesis _ Human and Artificial
# ───────────────────────────────────────────────────────────────


def section(title):
    """Print a formatted section header."""
    print("\n" + "=" * 65)
    print(f"  {title}")
    print("=" * 65)


def subsection(title):
    print(f"\n--- {title} ---")


# ============================================================
# STEP 0: LOAD AND PREPARE DATA
# ============================================================
section("STEP 0: LOADING DATA")
```