

Artificial Intelligence For Risk And Decision Assessment In Agile IT Projects: A Thematic Analysis And Dynamic Structuration Framework Approach

Aibek Karshiboev*, Khaled Al-Samad, Md Tanvir Rahman Tarafdar, Nur Nahar Rimi, Md Samirul Islam, Md Saidul Islam Papel, Azamat Mambetaliev

¹ *Department of Information Technology, Westcliff University, Irvine, CA 92614, USA.*

² *Department of Management Information Systems, International American University, Los Angeles, CA 90010, USA.*

**Correspondence: a.karshiboev.4633@westcliff.edu*

Abstract

The integration of artificial intelligence (AI) into Agile IT project management has emerged as a transformative strategy for enhancing risk assessment and decision-making processes. Despite the increasing interest, a fragmented understanding persists regarding the application, effectiveness, and limitations of AI-driven tools in Agile environments. This thematic review systematically analyses 20 peer-reviewed studies published between 2010 and 2025 to synthesise current knowledge and identify research gaps. The literature reveals that machine learning, predictive analytics, natural language processing, and reinforcement learning offer substantial benefits, including improved sprint planning, early risk detection, optimised resource allocation, and greater responsiveness to dynamic project demands. The study categorises findings into four core themes: AI integration in Agile workflows, AI-driven risk assessment methodologies, AI-enhanced decision support systems, and challenges to adoption. Barriers such as data quality issues, model interpretability, integration complexities, organisational resistance, and high implementation costs are critically examined. A conceptual framework, the Dynamic structuration framework (DSF), which leverages the adaptive structuration theory and Dynamic capability theory, is proposed to guide the structured integration of AI within Agile project lifecycles, emphasising the need for recursive co-evolution, iterative feedback loops, augmented capabilities as well as a governable human-AI collaboration. The review highlights the superiority of AI-driven approaches over traditional methods in terms of predictive accuracy and operational agility, while also calling for further empirical validation and development of explainable AI models. The findings offer valuable insights for researchers and practitioners seeking to advance AI-enabled Agile project management.

Keywords: Agile project management; artificial intelligence; risk assessment; decision-making; machine learning; thematic analysis.

1. Introduction

1.1 Background

The introduction of artificial intelligence (AI) in Agile IT project management has significantly changed how teams plan, execute, and monitor projects [1]. Existing Agile frameworks like Scrum [2], Kanban [3], and SAFe [4] encourage flexibility, iterative development, and continuous feedback. These frameworks allow teams to adjust quickly to changing requirements, making them useful in rapidly evolving IT environments. However, Agile methodologies face persistent challenges related to risk management, decision-making, and resource allocation, despite their adaptive capabilities [5–9]. Project teams often struggle with risk assessments, predicting potential bottlenecks or blockers, and making real-time, data-driven decisions [10].

AI offers a promising solution to these challenges by leveraging machine learning, predictive analytics, and natural language processing (NLP) [11], [12]. Machine learning

algorithms can analyse historical project data to identify trends and predict potential risks, enabling managers to take early, proactive measures. Predictive analytics improves decision-making by providing insights into project timelines, resource usage, and task prioritisation. Furthermore, NLP can streamline communication within Agile teams by automating documentation, analysing team interactions, and exposing potential concerns.

The growing complexity of modern IT projects further underscores the need for AI-driven project management. Many Agile projects involve cross-functional teams, stakeholders, and evolving requirements, making traditional risk assessment methods less effective [7]. Historically, Agile teams have relied on expert knowledge and intuition, which may not always provide timely or accurate insights. However, AI offers real-time monitoring, adaptive risk assessment, and intelligent automation to enable more effective project control [13].

Across industries, organisations are integrating AI into Agile methodologies to improve project outcomes, increase decision-making accuracy, and optimise resource allocation. By embedding AI-driven analytics into Agile workflows, teams can dynamically anticipate risks, adjust project plans, and improve overall success rates. This study explores how AI transforms Agile IT project management by enabling data-driven decision-making and operational efficiency.

1.2 Problem statement

Despite the growing adoption of AI in Agile project management, a significant gap remains in understanding how AI-driven risk assessment and decision-making impact Agile processes [14]. While AI-powered tools promise enhanced efficiency, predictive accuracy, and automated decision support, organisations often encounter challenges in fully utilising these technologies [15]. Data bias, model interpretability, and the seamless integration of AI into Agile workflows pose substantial hurdles to widespread adoption.

One of the critical concerns is data bias, where AI models trained on historical project data may reinforce existing inefficiencies or fail to adapt to evolving Agile environments [16]. The interpretability of AI-driven insights also presents challenges, as Agile teams require transparent and explainable models to make informed decisions. Furthermore, integrating AI into Agile frameworks requires overcoming technical, cultural, and operational barriers, including resistance to automation, upgrading of skills, and alignment of AI-driven recommendations with Agile principles of flexibility and human-centric collaboration.

While numerous studies explore AI applications in traditional project management methodologies [17]– [19], limited research has focused specifically on Agile environments. Agile projects differ substantially from conventional approaches due to their iterative nature, rapid development cycles, and continuous feedback mechanisms. As a result, existing AI-based project management solutions may not be directly applicable to Agile methodologies without significant adaptation.

This literature review addresses these gaps by synthesising current research, evaluating AI methodologies tailored for Agile project management, and identifying critical knowledge gaps. By providing a structured analysis of current trends, challenges, and best practices, this study aims to guide future research and industry adoption, ultimately facilitating the effective integration of AI into Agile project management for enhanced risk assessment and decision-making processes.

1.3 Rationale and significance

The rationale for this study lies in the urgent need to modernise risk management practices in Agile IT projects. While effective in stable environments, traditional risk assessment methods often fail to keep up with the rapid iteration and evolving risk profiles typical of Agile projects. Agile methodologies demand real-time adaptability,

iterative decision-making, and continuous risk assessment, which conventional approaches may not adequately support.

Integrating AI presents an opportunity to transition from reactive to proactive risk management. AI-driven tools such as predictive analytics and machine learning models can analyse historical project data, monitor real-time performance metrics, and flag emerging risks before they escalate into critical issues. NLP further enables automated insights from project documentation and team communications, providing Agile teams with timely, relevant information to improve decision-making processes.

By synthesising the current state of the literature, this review aims to:

1. Identify emerging trends and best practices for implementing AI in Agile project management.
2. Evaluate the efficacy of AI-driven risk assessment tools compared to traditional approaches.
3. Highlight the challenges and limitations of adopting AI in Agile settings, including data privacy, ethical concerns, and integration complexity.
4. Propose directions for future research that address unresolved gaps in current methodologies.

The significance of this review is twofold. Academically, it contributes to the theoretical understanding of integrating AI with Agile methodologies, providing a foundation for future empirical research. It explores how AI-driven solutions align with Agile principles and impact risk assessment, decision-making, and overall project performance. Practically, it offers IT project managers and industry practitioners insights into using AI tools to enhance risk mitigation, improve project outcomes, and drive competitive advantage in an increasingly dynamic technological landscape.

1.4 Research question

Based on the identified problem, this study seeks to answer: How has artificial intelligence (AI) been leveraged in Agile IT project management to enhance risk assessment and decision-making, and what are the key challenges and future directions identified in existing literature?

1.5 Research objectives

To address the research question, this literature review aims to:

1. Identify and categorise existing literature on AI applications in Agile IT project management, focusing on risk assessment and decision-making processes.
2. Critically evaluate the methodologies used in traditional and AI-driven risk assessment approaches within Agile projects, comparing their strengths and weaknesses.
3. Synthesise key findings regarding the efficacy of AI-driven tools in improving decision-making and mitigating risks, and assess how these findings influence project performance.
4. Identify gaps in the current literature and propose areas for future research that could address theoretical and practical shortcomings.
5. Propose a conceptual framework integrating AI capabilities with Agile project management practices to facilitate more robust risk assessment and decision-making strategies.

1.6 Scope and limitations

This review covers literature published between 2010 and 2025, reflecting recent advances in Agile methodologies and AI technologies. The focus is on empirical studies, theoretical frameworks, and case studies exploring AI applications in Agile IT project environments for risk assessment and decision-making. The key themes explored include AI methodologies, risk assessment techniques, decision-making processes,

implementation challenges, and future trends in Agile IT project management. Limitations of this review include:

- Restriction to the past decade and a half may exclude seminal works published before 2010 that could offer foundational insights.
- The diverse nature of research designs (qualitative, quantitative, and mixed methods) may pose challenges in synthesising findings into a unified framework.
- Rapid advancements in AI technology mean that the literature requires continuous updates to remain current.

1.7 Organisation of the study

The remainder of this study is organised as follows. Section 2 presents the methodology, including the literature search strategy, selection criteria, and thematic analysis approach. Section 3 presents the findings structured around key themes relating to AI integration, risk assessment, and decision-making in Agile IT project management. Section 4 discusses the results and highlights implications for theory and practice. Section 5 critically evaluates the results and highlights implications for theory and practice. Section 6 concludes with recommendations for future research and outlines the study's limitations.

2. Materials and methods

This study adopted a thematic review methodology to synthesise existing literature on the application of artificial intelligence (AI) in enhancing risk assessment and decision-making within Agile IT project management. The approach was interpretative and flexible, allowing for an in-depth exploration of emerging trends and conceptual contributions. The methodology encompassed several key stages: conceptual framing, literature search, study selection, data extraction, thematic synthesis, and quality assessment.

2.1 Conceptual framing

The review was guided by two established frameworks: FINER (Feasible, Interesting, Novel, Ethical, Relevant) and an adapted version of PICOT (Population, Intervention, Comparison, Outcome, Time). The FINER framework ensured that the research question was focused, significant, and ethically grounded, while also contributing novelty to the field of AI-driven Agile project management.

The adapted PICOT model framed the research scope by defining the population (Agile IT project teams), the intervention (AI-driven risk assessment and decision-making tools), the comparison (traditional risk assessment approaches), the outcome (project performance and decision-making efficacy), and the time frame (literature published between 2010 and 2025). These frameworks facilitated a structured and comprehensive analysis of how AI capabilities are applied in Agile project management contexts.

2.2 Literature search strategy

A comprehensive exploratory search was conducted across multiple academic and industry databases to capture relevant studies. The primary academic sources included IEEE Xplore, ACM Digital Library, Scopus, Web of Science, and Google Scholar. Additionally, pertinent industry reports, white papers, and conference proceedings were considered to encompass practical perspectives and emerging trends in AI applications for Agile project management. To ensure comprehensive coverage, a combination of keywords and Boolean operators was employed. Filters were applied to restrict results to peer-reviewed journal articles, high-quality conference papers, and reputable industry reports. The primary search strings included are:

- ("Artificial Intelligence" OR "Machine Learning" OR "AI-driven") AND ("Agile Project Management" OR "Scrum" OR "Kanban" OR "SAFe") AND ("Risk Assessment" OR "Project Risk" OR "Risk Mitigation")

- ("AI in Agile Project Management") AND ("Decision-Making" OR "Predictive Analytics")
- ("AI-driven Risk Management") AND ("Agile IT Projects")
- ("Machine Learning" OR "Predictive Analytics") AND ("Agile" AND "Decision-Making")

2.3 Study selection and eligibility criteria

As illustrated in Fig. 1, the study selection process followed a structured multi-stage screening procedure, beginning with 72 records identified from the databases. After duplicate removal, 65 unique records remained for title and abstract screening.

Titles and abstracts were screened for relevance to AI and Agile IT project management, resulting in the exclusion of 25 records that did not address the research focus on AI-driven risk assessment or decision-making. The remaining 40 full-text articles were assessed for eligibility. A further 20 articles were excluded due to factors such as conceptual overlap, a non-Agile scope, or absence of AI application. Ultimately, 20 studies were included in the final thematic synthesis.

Inclusion criteria:

- Publications dated between 2010 and 2025.
- Articles published in English.
- Empirical studies, conceptual frameworks, case studies, or theoretical discussions addressing AI in Agile IT project management.
- Research exploring AI-driven risk assessment, decision-making, machine learning, predictive analytics, natural language processing, or integration challenges in Agile environments.
- Peer-reviewed journal articles, conference papers, and reputable industry reports.

Exclusion criteria:

- Studies focused exclusively on traditional (non-Agile) project management methodologies.
- Publications that do not address AI applications within project management.
- Opinion pieces, editorials, or non-peer-reviewed sources.
- Articles published in languages other than English.

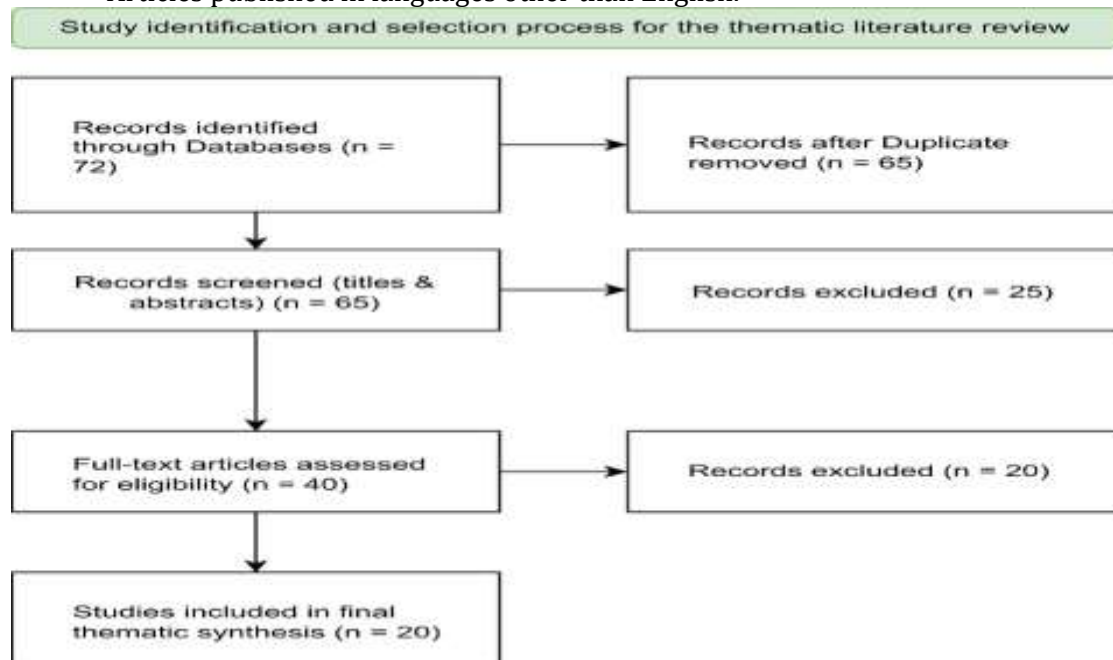


Fig. 1. Study identification and selection process for the thematic literature review

2.4 Data extraction and thematic synthesis

Key data were extracted from each study to support the thematic analysis. For each article, the following information was recorded: bibliographic details; study design and methodology; AI techniques and tools (e.g., machine learning algorithms, predictive models, natural language processing); Agile methodologies examined (e.g., Scrum, Kanban, SAgile); AI contributions to risk assessment and decision-making; and reported outcomes, challenges, and recommendations for future research.

The extracted data were manually coded and analysed to identify recurring patterns, common themes, and differences across studies. This enabled a rich and contextually grounded interpretation of the literature.

The synthesis followed a thematic analysis approach. Studies were categorised into four major themes: AI-driven risk assessment methodologies; AI-supported decision-making frameworks; implementation challenges and best practices; and emerging trends in AI-enhanced Agile methodologies. Rather than statistical meta-analysis, an interpretative synthesis approach was used to draw connections between methodologies and findings.

2.5 Quality assessment

The quality and credibility of each study were evaluated based on study design robustness and the strength of evidence. Attention was given to potential biases in data collection and analysis, particularly relating to data bias and model interpretability. Studies were also appraised for their contribution to understanding the role of AI in improving risk assessment and decision-making in Agile IT project management. No study was excluded solely on methodological limitations; instead, these limitations were documented to ensure a balanced interpretation.

2.6 Methodological limitations

Several limitations were acknowledged. Publication bias may have led to an over-representation of positive findings. Diversity in study designs and reporting styles posed challenges to developing a cohesive narrative. Rapid advancements in AI technologies may have resulted in the omission of recent developments. Finally, the manual nature of the thematic coding process introduced potential subjectivity, which was mitigated through repeated validation of the coding framework.

3. Thematic analysis

This chapter presents the findings of the thematic analysis conducted on the selected literature. Using Braun and Clarke's six-phase framework [79], the analysis identified four dominant themes, each representing critical dimensions of how artificial intelligence (AI) is integrated and applied in Agile IT project management: (i) AI integration in Agile IT project management, (ii) AI-driven risk assessment methodologies, (iii) AI-enhanced decision-making processes, and (iv) implementation challenges and limitations. To aid clarity, the thematic map illustrating the interrelationship between the four core themes identified through this analysis is presented in Fig. 2.

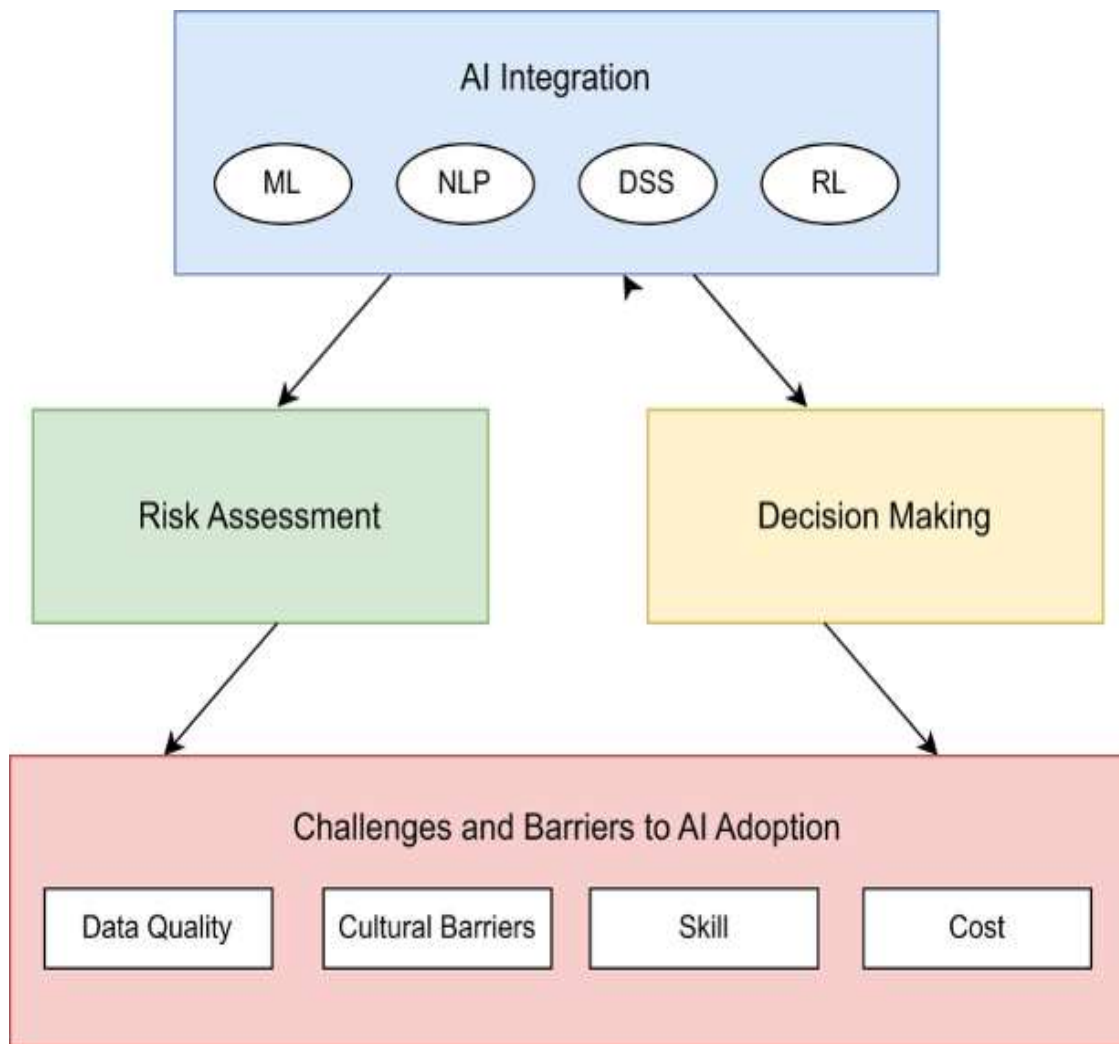


Fig. 2. Thematic map illustrating the interrelationship between the core themes of AI in Agile IT

3.1 AI integration in agile IT project management

The integration of AI into Agile IT project management represents a significant transformation in how projects are conceptualised, executed, and controlled. Studies consistently highlight how the convergence of computational techniques such as machine learning, natural language processing (NLP), and predictive analytics provides Agile teams with tools to analyse both historical and real-time data to inform decision-making processes [12], [22-24]. Agile environments, characterised by short iterative cycles and continuous feedback, are particularly suited to the dynamic capabilities of AI technologies [12].

Several case studies illustrate how organisations have successfully incorporated AI into Agile frameworks such as Scrum and Kanban. In these environments, AI-powered analytics platforms have been used to monitor team performance, predict sprint outcomes, and dynamically adjust project backlogs [25]. Real-time dashboards, enabled by embedded AI modules, offer insights into task completion rates, bottleneck identification, and workload optimisation [25].

The literature also identifies key AI tools that have facilitated these enhancements. Predictive models including decision trees, random forests, linear and logistic regression, support vector machines (SVM), and k-nearest neighbour (KNN) algorithms have been

applied to project risk and delay forecasting based on historical datasets [26]–[30]. NLP applications within Agile ecosystems automate documentation and detect potential issues through sentiment analysis in communication tools such as Slack and Jira [31]. Reinforcement learning approaches further enhance resource allocation and sprint planning by learning from continuous project feedback [32].

Decision support systems (DSS) also represent a critical AI-driven innovation for Agile teams. Table 1 presents a synthesis of DSS platforms and AI-powered task allocation tools identified across the literature [33].

Table 1. AI-powered decision support systems for agile task allocation, sprint planning, and resource distribution

Tool/Platform	Key Features	Optimization	Reference
SmartTask by Miro	AI prioritizes tasks and optimizes sprint planning.	Automates task allocation based on team member skills, workloads, and task complexity.	Miro - SmartTask
JIRA + AI-based Plugins	Integrates AI plugins for resource allocation and sprint planning.	Suggests task prioritization, identifies risks, and recommends task assignments based on team strengths.	Atlassian JIRA
Agile AI by ThoughtWorks	Predictive analytics for sprint outcomes, bottleneck identification.	Optimizes task allocation and resource distribution based on historical sprint data.	ThoughtWorks Agile AI
Monday.com (AI-driven)	AI-powered project management with intelligent scheduling and task assignment.	Allocates tasks based on team performance, workload, and skillsets.	Monday.com AI
Trello + Butler Automation	AI-driven automation for task assignments and sprint planning.	Automates task distribution based on past performance and predicts task priorities.	Trello Butler Automation
Forecast by Planbox	AI-powered resource and project management.	Predicts timelines, resources, and optimal team assignments for tasks.	Forecast by Planbox
Scrumwise (Agile Analytics)	AI analytics for sprint velocity and team performance tracking.	Optimizes sprint planning and resource allocation based on team dynamics and historical data.	Scrumwise
Targetprocess with AI	AI for sprint planning and task allocation.	Forecasts sprint goals and task assignments based	Targetprocess

		on team capacity and historical data.	
RescueTime + AI	Tracks team productivity and time usage.	Provides data to optimize task allocation by identifying team members' productive patterns.	RescueTime
ClickUp (Smart Scheduling)	AI-powered Smart Scheduling and resource allocation.	Assigns tasks based on member availability, skills, and past sprint data for optimal task distribution.	ClickUp

Note. The software tools listed in this table are commercial products. Descriptions are based on publicly available information from the vendors' official websites as of May 2025. No endorsement by the authors is implied.

3.2 AI-Driven risk assessment methodologies

A substantial proportion of the reviewed literature focuses on the application of AI to risk identification, forecasting, and mitigation within Agile environments [37]–[45]. Traditional risk assessment in Agile projects relies on manual tracking and expert reviews, which are often inadequate in rapidly changing project contexts [12].

AI-based risk identification methodologies address this gap by deploying predictive analytics, anomaly detection, probabilistic modelling, and NLP techniques. Supervised learning approaches such as decision trees and random forests forecast potential delays and cost overruns [37]. Unsupervised learning methods, including clustering algorithms segment projects into different risk categories, providing nuanced views of potential vulnerabilities [38]. Bayesian networks and fuzzy logic models have been used to update risk probabilities in real-time as new data emerge [39]–[41].

The role of NLP in risk assessment is also emphasised, with applications capable of analysing unstructured project communication to detect emerging risks or negative sentiment trends [42]. Deep learning architectures such as recurrent neural networks (RNNs) have proven valuable for analysing time-series data from Agile sprints to detect subtle risk signals [43].

Numerous authors report the practical success of these methods. AI-powered risk dashboards offer real-time visualisation and alert generation to assist project managers with proactive risk mitigation [44], [45]. The overall process flow of an AI-driven risk assessment system, as commonly reported in the literature, is illustrated in Fig. 3, highlighting the sequential stages from data input through pre-processing and model training to risk scoring and dashboard alert generation.

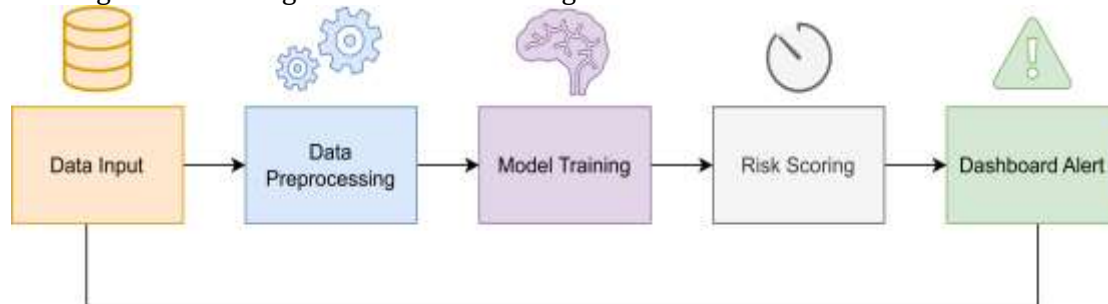


Fig. 3. AI-driven risk assessment pipeline

3.3 AI-enhanced decision-making in agile projects

The third key theme concerns how AI enhances decision-making capabilities in Agile teams [46]. Rapid, informed decision-making is essential within Agile methodologies due to continuous changes in scope and stakeholder demands. AI-driven systems enable Agile teams to translate large volumes of project data into actionable recommendations [12], [46].

As illustrated in Table 2, the literature identifies several specific approaches that help Agile teams reduce reliance on intuition and instead adopt evidence-based practices. Predictive analytics is extensively applied to simulate project trajectories and anticipate possible future scenarios [46]– [50]. DSS tools integrate real-time project data with historical knowledge to recommend optimal paths or resource allocations [33]. Scenario analysis and simulation techniques allow Agile teams to conduct “what-if” experiments and explore the impacts of different decisions [49], [50]. NLP further adds value by extracting critical insights from team communication logs [51], [52].

Table 2. Summary of technologies and their applications in decision-making

Technology	Description
Predictive Analytics	Analyzing historical data to forecast potential outcomes, enabling managers to evaluate various decision paths.
Automated Decision Support Systems (DSS)	Integrating diverse data sources, these systems provide real-time recommendations by simulating different scenarios.
Scenario Analysis and Simulation	"What-if" analyses allow teams to anticipate the impact of different decisions and prepare effective contingencies.
Natural Language Processing (NLP)	Processing unstructured data from team communications to extract insights that may affect decision-making.

Note. The technologies listed represent general methodological categories commonly reported in the reviewed literature. They are not specific to any proprietary software products.

The literature consistently reports key benefits of AI-enhanced decision-making in Agile settings, including faster and more accurate decisions [47], [48], greater recommendation reliability through data triangulation [46], enhanced risk anticipation via simulations [49], [50], and reduced cognitive bias through algorithmic objectivity [51], [52]. However, multiple studies note that data quality, model explainability, and organisational trust in automated recommendations remain critical prerequisites for effective adoption [44].

3.4 Challenges and barriers to AI adoption

Despite the numerous reported benefits, integrating AI technologies into Agile IT project management remains complex and presents several challenges. The literature identifies four broad categories of barriers: technical, organisational, cultural, and economic (summarised in Table 3) [44], [53]– [58].

Technical issues include poor data quality, incomplete datasets, and the presence of legacy systems that do not integrate effectively with AI platforms [44], [53], [54]. Data privacy and regulatory compliance, particularly adherence to the General Data Protection Regulation (GDPR), are also ongoing concerns for organisations implementing AI in Agile environments [55], [56].

At the organisational level, common obstacles include resistance to change among teams accustomed to traditional practices, limited AI expertise within Agile teams, and concerns over potential job displacement or an over-reliance on automation [12], [36], [57]. Moreover, reconciling the human-centric principles of Agile with the automated recommendations provided by AI systems presents a notable cultural alignment challenge [12], [36], [58].

Economic factors further compound these barriers, as the high costs associated with software licensing, infrastructure upgrades, staff training, and ongoing maintenance often discourage smaller organisations from adopting AI technologies [44]. Many studies advocate for a hybrid approach, whereby human expertise and AI tools operate collaboratively to maximise decision-making quality and maintain alignment with Agile principles [12], [36].

Table 3. Summary of reported challenges and barriers to AI adoption in agile IT project management

Category	Key Barriers	Reference
Technical and Data-Related	Poor data quality and incomplete datasets; legacy system integration issues; model interpretability; data privacy concerns (GDPR compliance)	[44], [53]– [58]
Organisational and Cultural	Resistance to change; skill gaps in AI expertise; fear of job displacement; alignment challenges with Agile principles	[12], [36], [57], [58]
Economic and Resource Constraints	High software and infrastructure costs; costly staff training; ongoing maintenance and upgrade burdens	[44]

4. Discussions and future directions

This section presents a critical discussion of the findings, focusing on emerging technological trends, theoretical and practical implications, comparative analysis of AI-driven and traditional approaches, as well as key limitations and directions for future research. The synthesis draws from the thematic analysis in Section 3 to provide a comprehensive evaluation of how AI continues to reshape Agile IT project management.

4.1 Emerging Trends in AI Technologies

The evolving capabilities of AI are creating significant opportunities for its application within Agile IT project environments. The literature highlights four major trends.

4.1.1 Advanced deep learning and reinforcement learning

Recent research explores the use of novel architectures such as recurrent neural networks and transformer-based models to enhance predictive accuracy and adaptability in Agile contexts [34], [55], [59]–[61]. Generative AI has been investigated for automating sprint planning and backlog creation tasks [34], [55], [59]– [61]. Reinforcement learning approaches have also been applied to optimise resource allocation and dynamic sprint strategies, showing promising results for improving project responsiveness [62]–[64].

4.1.2 Explainable AI (XAI)

The increasing complexity of AI models has intensified the demand for transparency and interpretability. The literature identifies explainable AI (XAI) as a critical research

priority to ensure that stakeholders can understand and trust AI-driven recommendations [44], [65]–[67]. XAI methods aim to demystify complex models by offering insights into how predictions are made, thereby supporting informed decision-making in Agile project environments. Table 4 summarises leading XAI techniques and their potential applications in the context of Agile IT project management.

Table 4. Summary of popular explainable AI (XAI) techniques and their potential applications in agile project management

XAI Technique	Description	Reference
Shapley Additive Explanations (SHAP)	Assigns each feature an importance value for a given prediction, aiding understanding of the contributions of individual variables.	[68]
Local Interpretable Model-Agnostic Explanations (LIME)	Approximates complex models with simpler, interpretable models locally around the prediction to explain individual outcomes.	[69]
Feature Manipulation	Systematically alters input features to observe changes in predictions and identify key factors influencing model outputs.	[70]
Visualisation Techniques	Uses decision trees, heatmaps, or partial dependence plots to visually illustrate model behaviour and decision pathways.	[71]

4.1.3 Integration with IoT and Big Data

AI's convergence with the Internet of Things (IoT) and big data facilitates more comprehensive data integration and real-time project monitoring [72]. This development has the potential to significantly enhance risk detection, task allocation, and performance tracking within Agile teams.

4.1.4 Hybrid human-AI collaboration

Recent studies indicate a shift towards collaborative systems that combine human expertise with AI-generated insights [73], [74]. These emerging models aim to optimise decision-making by balancing automated recommendations with human contextual understanding.

4.2 Theoretical implications

The convergence of AI and Agile methodologies necessitates the reconsideration of traditional project management theories. Data-centric decision-making, predictive analytics, and adaptive learning are disrupting conventional models based on static planning and expert intuition. AI-driven approaches support continuous forecasting, real-time risk assessment, and dynamic resource allocation, which contrast sharply with the rigid phase-based processes of traditional methodologies [79], [80]. However, challenges such as cultural resistance and the need for significant infrastructural and training investments remain [13], [16], [75]. The integration of AI into Agile environments also raises important theoretical questions regarding the balance between human judgement and algorithmic recommendations, and how this evolving relationship may redefine established principles of project governance and leadership in future research.

4.3 Practical implications

The practical benefits of AI integration within Agile IT project management are widely acknowledged across the literature. A primary advantage is enhanced monitoring and forecasting, where AI-powered dashboards and predictive analytics tools provide

continuous oversight of project metrics, enabling early identification of potential risks and bottlenecks before they escalate into critical issues.

In addition, AI facilitates optimised decision-making. Automated decision support systems minimise reliance on subjective human judgement, thereby improving both the speed and accuracy of decisions made in response to dynamic project requirements. These systems allow for timely interventions, ultimately supporting Agile principles of rapid adaptability and responsiveness to change.

Furthermore, AI-driven models have been shown to improve resource allocation and risk mitigation. By dynamically reallocating resources based on real-time project data and generating automated recommendations for risk responses, these tools contribute significantly to the achievement of overall project objectives and the enhancement of project performance.

4.4 Comparison of AI-driven and traditional methods

The comparative analysis confirms that AI-driven approaches offer substantial advantages over traditional methods. Table 5 summarises the core differences.

Table 5 Comparison of AI-driven vs. traditional methods

Aspect	AI-Driven Approach	Traditional Approach
Data Processing	Automated large-scale data analysis	Manual data handling with lower scalability
Predictive Capabilities	Proactive real-time risk identification	Reliance on historical data and periodic reviews
Decision-Making	Data-driven, consistent, and objective	Subjective and prone to human bias
Response Time and Agility	Real-time monitoring and rapid intervention	Delayed responses due to manual processes
Adaptability	Continuously updates and adapts	Rigid and slower to adapt
Implementation Complexity	Higher technical and cultural challenges	Lower complexity but limited scalability
Cost-Efficiency	Automation reduces human effort	Manual processes increase operational costs

Studies report that AI-enhanced Agile teams have achieved superior project outcomes, such as an 18.3% reduction in sprint completion time and a 23.1% improvement in task allocation accuracy [33], [76], [77]. AI-driven models also predicted sprint overruns with 81.2% accuracy compared to 59.6% with traditional methods [76].

To provide a visual comparison of these performance aspects, Fig. 4 presents a radar chart illustrating the relative strengths of AI-driven versus traditional project management approaches across the seven key performance dimensions summarised in Table 5. As shown, AI-driven approaches consistently outperform traditional methods in data processing, predictive capabilities, decision-making consistency, response time, and adaptability, while traditional methods retain relative simplicity in implementation.



Fig. 4. Comparison of AI-driven and traditional project management methods

4.5 Limitations and gaps in the Literature

Despite the growing body of research, several gaps and limitations persist within the current literature on AI-driven Agile project management. Firstly, many AI models remain insufficiently validated against real-world project data, which constrains their practical applicability and limits their acceptance within industry practice [75]. Additionally, there is a notable lack of universally accepted evaluation metrics, making it difficult to compare AI-assisted Agile processes across different industries and contexts [78]. The effectiveness of AI models also remains highly dependent on the availability and quality of underlying datasets, with poor data inputs potentially compromising predictive accuracy and decision-support reliability.

Current research further provides limited comprehensive frameworks capable of fully integrating AI technologies across multiple project management knowledge areas, such as risk, cost, scheduling, and stakeholder management. Moreover, there is a scarcity of longitudinal studies assessing the long-term impacts of AI adoption on project outcomes and organisational performance, which leaves important questions about sustainability and scalability unanswered. Finally, the complex interplay between human expertise and AI-generated recommendations remains underexplored, with little empirical work to understand how best to optimise collaborative decision-making between human and AI agents in Agile environments.

6. A Dynamic Structuration Framework for AI-Enabled Agile Project Management

The thematic analysis uncovers a significant gap in understanding how artificial intelligence reshapes Agile project ecosystems. While the existing literature discusses technical applications, it does not address the fundamental changes that occur when AI becomes a key part of Agile methodologies instead of just a tool. This session seeks to fill the gap by proposing the Dynamic Structuration Framework (DSF), which combines Adaptive Structuration Theory (AST) and Dynamic Capabilities Theory (DCT). It provides crucial insight into the ongoing interaction between AI technologies, organisational structures, and adaptive abilities in Agile settings. The framework views AI-Agile integration as a socio-technical co-evolution where human and algorithmic intelligence support and shape each other.

6.1 Theoretical Foundation and Rationale

The AI-Agile integration represents a paradigm shift, challenging traditional project management's mechanistic worldview. According to [81], the AST is a crucial framework that gives critical insights into how teams appropriate technologies through three distinct patterns: faithful appropriation, where technologies are used as designed, adaptive appropriation in which technologies are modified to fit local contexts, and ironic appropriation that entails using technologies in ways that contradict their intended purpose. These patterns demonstrate how appropriation is fundamentally hermeneutic, requiring continuous interpretation and negotiation between human practices and technological capabilities.

The DCT explains provides insight on capability amplification through its focus on sensing, seizing, and transforming organisational competencies [82]. When combined with AI technologies, these dynamic capabilities become reconstituted through algorithmic amplification, acceleration of the decision-making process, as well as an enhanced ability to anticipate future trends. This proposed DSF essentially addresses AST's under-specification of capability evolution and the inherent neglect of technological constitution of the DCT's framework.

6.2 The Dynamic Structuration Framework

The DSF reimagines AI-Agile management as a complex adaptive system with three recursively interacting dimensions that operate simultaneously to generate emergent organisational capabilities:

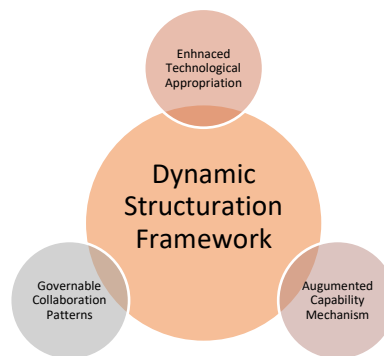


Fig. 5. Dynamic Structuration Framework for AI-Enabled Agile Project Management

6.2.1 Enhanced Technological Appropriation Structures

The framework's main strength is in seeing technological appropriation as a process where human interpretation and algorithmic abilities develop together. Nonetheless, it becomes quite important to have recursive structuring mechanisms in practice, and this could be a robust feedback loop between AI outputs and human decisions to identify clear triggers, like sprint review performance thresholds, data pathways, such as Jira-to-ML pipeline integrations, and validation protocols. During sprint retrospectives, when velocity metrics differ by a defined amount from predictions, an automated model retraining using updated task-completion datasets is retriggered. This approach would undoubtedly shine over the traditional approach by turning abstract structuration cycles into practical processes.

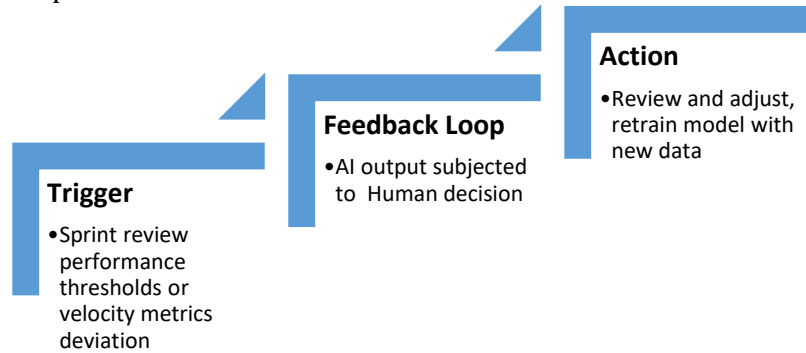


Fig. 6. Enhanced Technological Appropriation structures in DSF

6.2.2 Augmented Capability Mechanisms

While the DSF correctly identifies the role of AI in improving capabilities, leaning further into the distributed cognition theory can provide further insight into augmented dynamic capabilities, as it provides insight into how cognitive responsibilities move between human and artificial agents during sensing activities [83]. Consequently, in this framework, while technologies such as NLP systems always analyse Slack messages for risk sentiment, product owners are required to keep contextual understanding of the flagged phrases, ushering a combined thinking or collaborative intelligence where the shared output from AI-enabled large-scale pattern recognition, and human-based context provides the shared outputs guide for backlog updates.

6.2.3 Governable Collaboration Patterns

The governance structure in the DSF frameworks effectively tackles ethical issues using "distributed responsibility matrices," but it needs measurable compliance indicators. As such, we suggest expanding this with clear audit protocols:

Table 6. Overview of Decision Tiers for the DSF

Decision Tier	Human Oversight Mechanism	Algorithmic Transparency
Strategic (release planning)	Ethical review board veto rights	SHAP values for feature importance
Tactical (sprint prioritisation)	Product owner explainability sessions	LIME local interpretations
Operational (task assignment)	Developer adversarial testing	Real-time fairness monitoring

The proposed DSF no doubt goes beyond similar theories with its recursive co-evolution model. However, it needs to address conflicts with sociometrical perspectives. The DSF clearly shows how algorithmic learning drives capability development through three reinforcing cycles:

Table 7. Development Cycles of the DSF

State	Cycle	Description
1	Interpretative cycles	Teams understand AI outputs during backlog grooming
2	Materialization	where adapted practices are integrated into tool settings
3	Validation cycles	where results guide model retraining. This three-part structure resolves the agency paradox by showing how humans and algorithms work together to shape Agile practices instead of just interacting

6.3 Key Theoretical Advances of the DSF

1. Symbiotic Intelligence: Unlike sociomateriality's focus on entanglement [84], DSF theorises how human-AI collaboration creates new cognitive abilities that surpass the capabilities of individual components.

2. Recursive Structuration: This concept builds on AST by explaining how AI systems learn and lead to ongoing structural changes instead of a one-time adjustment.

3. Augmented Dynamic Capabilities: This expands DCT by identifying AI-specific capability mechanisms [85], such as algorithmic amplification, temporal compression, and predictive anticipation, which traditional theory cannot clarify.

4. Ethical Co-constitution: This approach tackles the innovation-responsibility conflict by including ethical safeguards within the theoretical framework instead of seeing them as separate restrictions.

The framework addresses the agency paradox with "distributed responsibility matrices," which are tools that assign accountability for decisions across human-AI interfaces based on the context and ethical risk levels.

6.4 Practical Implementation Framework

The DSF operationalisation requires focused attention on three connected areas; as such, the following implementation framework is proposed.

Table 8. Implementation framework for the DSF

Strategy	Description
Appropriation Strategy Development	Conducting "appropriation retrospectives" to map usage patterns from faithful to adaptive to ironic
	Hosting workshops that find successful ironic uses for scaling
	Building skills for "algorithmic coevolution literacy"
Capability Scaffolding	Pair programming sessions with AI code generation tools, which aligns with [86]
	Collaborative human-AI design thinking workshops for feature ideas

	Ongoing capability assessments using matrices that track the development of shared intelligence
Governance Instrumentation	Real-time dashboards for monitoring fairness
	Audit trails for algorithms to ensure accountability in decisions

The framework emphasises that successful implementation requires moving beyond simple technology adoption to fundamental organisational transformation that addresses appropriation strategies, capability development, and governance innovation simultaneously.

6.6 Empirical Validation Protocol

Future research must adopt novel methodologies to capture the dynamic properties of AI-enabled organisational transformation:

Table 9. Validation Framework for Core Constructs

Construct	Measurement Approach	Validation Metric
Appropriation Maturity	Observed adaptation frequency across faithful/adaptive/ironic patterns	Ratio of ironic to faithful appropriation instances per sprint cycle
Augmented Sensing	Risk detection latency comparison between AI-augmented and traditional approaches	Time-to-awareness differential for emerging project risks
Governance Legitimacy	Perceived accountability and trust in hybrid decision-making processes	

We also propose the following hypotheses for empirical validation:

Table 10 Hypothesis for empirical validation

Hypothesis	Overview
H ₁	Teams with higher rates of ironic appropriation will show better innovation outcomes due to improved sensing abilities.
H ₂	Implementing governance tools will predict improvements in ethical compliance without slowing down sprint speed.
H ₃	Progressing through appropriation phases will relate to the growth of capabilities and better performance.

These propositions provide concrete directions for empirical research while maintaining theoretical rigour and practical relevance.

6.7 Limitations and Future Extensions

Despite the framework's potential to fill the gaps in the systematic review, it is important to note that the framework was developed mainly from literature in Western organisational contexts, which inherently possesses a limitation in terms of generalizability in different cultural settings. Beyond this, the focus is on machine learning and natural language processing applications; as such, new technologies might require adjustments to the framework.

It is also important to mention that the framework requires advanced AI development processes and good data management. Beyond this, it relies on psychological safety, which allows for experimentation and appropriate use. Furthermore, it shows the strongest effects after several rounds of adjustment and learning.

Future Research Priorities

1. Cross-cultural Validation: Examining how the framework applies in collectivist and individualist cultures and various regulatory settings.
2. Generational Analysis: Investigating how new generative AI tools speed up the development of capabilities beyond current theories.
3. Sector-specific Adaptations: Creating different framework versions for regulated industries with varying risk levels and compliance needs.

The framework's theoretical contributions lay the groundwork for further development as AI technologies and organisational practices evolve together.

6.8 Conclusion

This thematic analysis argues that the potential of AI in Agile risk and decision assessment depends on rethinking the AI-Agile relationship beyond just tool adoption. The proposed Dynamic Structuration Framework (DSF), connects adaptive structuration and dynamic capability theories to address the interaction between AI tools, Agile processes, and organisational learning. This framework sees AI as a driver for joint evolution, turning static risk models into dynamic systems shaped by iterative feedback and flexible governance. We believe that effective AI integration involves developing organisational skills, ongoing adaptation, teamwork in understanding, and ethical oversight, supported by the DSF. The innovation lies in viewing AI adoption as a journey to build capabilities, emphasising human judgment and adaptability. Future efforts should focus on this collaborative evolution, ensuring AI enhances, rather than replaces, agile's fundamental responsiveness in changing project environments.

Funding: No funding is available for this study.

Conflict of Interest: The author(s) have no conflicts of interest to declare

1. Aibek Karshiboev*, College of Technology & Engineering, Westcliff University, 17877 Von Karman Ave, 4th floor, Irvine, CA 92614, USA. Email: a.karshiboev.4633@westcliff.edu, ORCID ID: 0009-0006-9094-8509
2. Mahfujur Rahman Faraji, Department of Engineering Management, Westcliff University, Irvine, CA 92614, USA. Email: m.faraji.214@westcliff.edu, Orchid ID: 0009-0004-2312-2622
3. Md Tanvir Rahman Tarafdar, Department of Information Technology, Westcliff University, Irvine, CA 92614, USA. Email: t.tarafdar.208@westcliff.edu, Orchid ID: 0009-0007-1391-6201
4. Nur Nahar Rimi, Department of Information Technology, Westcliff University, Irvine, CA 92614, USA
Email: N.rimi.253@westcliff.edu, Orcid ID: 0009-0002-8130-5721
5. Md Samirul Islam, Department of Management Information Systems, International American University
Los Angeles, CA 90010, USA, Email: m.islam.265@westcliff.edu, Orchid ID: 0009-0001-2097-1483
6. Md Saidul Islam Papel, Department of Management Information Systems, International American University, Los Angeles, CA 90010, USA. Email: mdpapeldu@gmail.com, Orchid ID: 0009-0006-1358-5740

7. Azamat Mambetaliev, College of Technology & Engineering, Westcliff University, 17877 Von Karman Ave, Irvine, CA 92614, USA. Email: a.mambetaliev.2674@westcliff.edu, ORCID ID: 0009-0007-8524-6761

References

- 1 H.K. Dam, T. Tran, J. Grundy, A. Ghose, Y. Kamei, Towards effective AI-powered agile project management, in: 2019 IEEE/ACM 41st International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER), IEEE, 2019, pp. 41–44.
- 2 A. Srivastava, S. Bhardwaj, S. Saraswat, SCRUM model for agile methodology, in: 2017 International Conference on Computing, Communication and Automation (ICCCA), IEEE, 2017, pp. 864–869.
- 3 M.O. Ahmad, J. Markkula, M. Oivo, Kanban in software development: A systematic literature review, in: 2013 39th Euromicro Conference on Software Engineering and Advanced Applications, IEEE, 2013, pp. 9–16.
- 4 W. Hussain, et al., How can human values be addressed in agile methods? A case study on SAFe, IEEE Trans. Softw. Eng. 48 (12) (2022) 5158–5175.
- 5 B. Alsaadi, K. Saeedi, Data-driven effort estimation techniques of agile user stories: A systematic literature review, Artif. Intell. Rev. 55 (7) (2022) 5485–5516.
- 6 S.K. Khurana, M.A. Wassay, Towards challenges faced in agile risk management practices, in: 2023 International Conference on Inventive Computation Technologies (ICICT), IEEE, 2023, pp. 937–942.
- 7 K. Bugarová, J. Šimíčková, Risk management in traditional and agile project management, Transp. Res. Procedia 40 (2019) 986–993.
- 8 I. Ghani, A. Lim, M. Hasnain, I. Ghani, M.I. Babar, Challenges in distributed agile software development environment: A systematic literature review, KSII Trans. Internet Inf. Syst. 13 (9) (2019) 4555–4571.
- 9 W.R. Fitriani, P. Rahayu, D.I. Sensuse, Challenges in agile software development: A systematic literature review, in: 2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS), IEEE, 2016, pp. 155–164.
- 10 M.A. Rahaman, F.Z. Rozony, M.S.A. Mazumder, M.N. Haque, M.A. Rauf, Big data-driven decision making in project management: A comparative analysis, Acad. J. Sci. Technol. Eng. Math. Educ. 4 (3) (2024) 44–62.
- 11 H. Lei, W. Lai, W. Feaster, A.C. Chang, Artificial intelligence and agile project management, in: Intelligence-Based Cardiology and Cardiac Surgery, Elsevier, 2024, pp. 401–405.
- 12 S. Chinta, The impact of AI-powered automation on agile project management: Transforming traditional practices, Int. Res. J. Eng. Technol. 8 (10) (2021) 2025–2036.
- 13 Z. Jin, Integrating AI into agile workflows: Opportunities and challenges, Appl. Comput. Eng. 116 (2024) 49–54.
- 14 E. Öztemel, Y. Tuncer, Review of AI in project management and conceptual analysis on risk management, in: Engineering and Technology Management in Challenging Times, Springer, 2024, pp. 221–237.
- 15 V. Saklamaeva, L. Pavlič, The potential of AI-driven assistants in scaled agile software development, Appl. Sci. 14 (1) (2023) 319.
- 16 E.K. Zadeh, A.B. Khoulenjani, M. Safaei, Integrating AI for agile project management: Innovations, challenges, and benefits, Int. J. Ind. Eng. Constr. Manag. 1 (1) (2024) 1–10.
- 17 F. Shoushtari, A. Daghighi, E. Ghafourian, Application of artificial intelligence in project management, Int. J. Ind. Eng. Oper. Res. 6 (2) (2024) 49–63.

- 18 S. Bushuyev, D. Bushuyev, V. Bushuyeva, N. Bushuyeva, Y. Tykchonovych, Strategic project management development under influence of artificial intelligence, *Bull. Natl. Tech. Univ. KhPI Ser. Strateg. Manag. Portf. Program Proj. Manag.* 1 (8) (2024) 3–7.
- 19 M.M.I. Shamim, Artificial intelligence in project management: Enhancing efficiency and decision-making, *Int. J. Manag. Inf. Syst. Data Sci.* 1 (1) (2024) 1–6.
- 20 S.R. Cummings, S.B. Hulley, *Designing clinical research: An epidemiologic approach*, Williams & Wilkins, 1988.
- 21 W.S. Richardson, M.C. Wilson, J. Nishikawa, R.S. Hayward, The well-built clinical question: A key to evidence-based decisions, *ACP J. Club* 123 (3) (1995) A12–A13.
- 22 D. Vergara, A. del Bosque, G. Lampropoulos, P. Fernández-Arias, Trends and applications of artificial intelligence in project management, *Electronics* 14 (4) (2025) 800.
- 23 P. Tupsakhare, Enhancing agile methodologies with AI: Driving efficiency and innovation, *Eur. J. Adv. Eng. Technol.* 9 (10) (2022) 66–71.
- 24 K.C. Lakshminarasimham, Technology leadership for program success: Integrating AI and agile methods for modern enterprises, in: *Integrating Blue-Green Infrastructure into Urban Development*, IGI Global, 2025, pp. 489–506.
- 25 V. Pantovic, M. Smigic, M. Djordjevic, D.A. Milovanovic, AI-powered agile project management in sustainable development of industry 4.0, in: *Intelligent and Sustainable Engineering Systems for Industry 4.0 and Beyond*, CRC Press, pp. 293–306.
- 26 C. Vasamsetty, B. Kadiyala, G. Arulkumaran, Decision tree algorithms for agile e-commerce analytics: Enhancing customer experience with edge-based stream processing, *Int. J. HRM Organ. Behav.* 7 (4) (2019) 14–30.
- 27 D.E. Wińska, E. Kot, W. Dąbrowski, Reducing the uncertainty of agile software development using a random forest, in: *Lean and Agile Software Development: 5th International Conference, LASD 2021, Virtual Event, January 23, 2021, Proceedings*, Springer, 2021, p. 145.
- 28 M.V.N. Hemrajani, V. V.N., Predicting effort of agile software projects using linear regression, ridge regression and logistic regression, 2021.
- 29 A. Najm, A. Zakrani, A. Marzak, An enhanced support vector regression model for agile projects cost estimation, *IAES Int. J. Artif. Intell.* 11 (1) (2022) 265.
- 30 E.R. Sánchez, H.C. Maceda, E.V. Santacruz, Software effort estimation for agile software development using a strategy based on k-nearest neighbors algorithm, in: *2022 IEEE Mexican International Conference on Computer Science (ENC)*, IEEE, 2022, pp. 1–6.
- 31 M.A. Quintana, R.R. Palacio, G.B. Soto, S. González-López, Agile development methodologies and natural language processing: A mapping review, *Comput.* 11 (12) (2022) 179.
- 32 R. Adel, H. Harb, A. Elshenawy, A multi-agent reinforcement learning risk management model for distributed agile software projects, in: *2021 Tenth International Conference on Intelligent Computing and Information Systems (ICICIS)*, IEEE, 2021, pp. 512–520.
- 33 S.S. Almalki, AI-driven decision support systems in agile software project management: Enhancing risk mitigation and resource allocation, *Syst.* 13 (3) (2025) 208.
- 34 A. Bahi, J. Ghari, Y. Gahi, Integrating generative AI for advancing agile software development and mitigating project management challenges, *Int. J. Adv. Comput. Sci. Appl.* 15 (3) (2024).
- 35 K.R. Alam, C. Barua, J.U.Z. Kabir, The future of agile: Utilizing AI together with

- machine study to support real time project control and modifying decision making, *J. Innov. Sci. Res. Technol.* 10. (1) (2025) 1004–1007.
- 36 I.W. Gamage, R. Rathnayake, T. Halloluwa, Estimating story points in scrum: Balancing accuracy and interpretability with explainable AI, in: 2024 6th International Conference on Advancements in Computing (ICAC), IEEE, 2024, pp. 139–144.
- 37 K. Moharrerri, A.V. Sapre, J. Ramanathan, R. Ramnath, Cost-effective supervised learning models for software effort estimation in agile environments, in: 2016 IEEE 40th Annual Computer Software and Applications Conference (COMPSAC), IEEE, 2016, pp. 135–140.
- 38 M.F.I. Khan, et al., Predictive analytics and machine learning for real-time detection of software defects, 2024.
- 39 S. Chatterjee, B. Maji, A Bayesian belief network-based model for predicting software faults in early phase of software development process, *Appl. Intell.* 48 (8) (2018) 2214–2228.
- 40 A. Saini, L. Ahuja, S.K. Khatri, Effort estimation of agile development using fuzzy logic, in: 2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), IEEE, 2018, pp. 779–783.
- 41 M. Perkusich, G. Soares, H. Almeida, A. Perkusich, A procedure to detect problems of processes in software development projects using Bayesian networks, *Expert Syst. Appl.* 42 (1) (2015) 437–450.
- 42 R. Younisse, M. Azzeh, Application of natural language processing techniques in agile software project management: A survey, in: 2023 14th International Conference on Information and Communication Systems (ICICS), IEEE, 2023, pp. 01–06.
- 43 H.K. Mittal, M. Arsalan, P. Garg, A novel deep learning model for effective story point estimation in agile software development, in: 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP), IEEE, 2024, pp. 404–410.
- 44 A. Bah Esseme, A. Faniyan, G. Farayola, et al., AI in project management: Enhancing efficiency, *Decis. Making Risk Manag. J. Artif. Intell. Mach. Learn. Data Sci.* 3 (1) (2025) 2107–2114.
- 45 E. Häikiö, J. Heikkilä, Adoption and governance of AI-powered dashboards in executive-level decision-making, 2024.
- 46 T. Dybå, T. Dingsøy, N.B. Moe, Agile project management, *Softw. Proj. Manag. Changing World* (2014) 277–300.
- 47 P. Tominc, D. Oreški, M. Rožman, Artificial intelligence and agility-based model for successful project implementation and company competitiveness, *Inf.* 14 (6) (2023) 337.
- 48 L.B. Williams, Artificial intelligence/machine learning as a tool for project management enhancement: A qualitative study on the future of technology in increasing the effectiveness of project managers, PhD Thesis, Capella University, 2024.
- 49 V. Božić, Intelligent and agile risk management, 2023.
- 50 G. Tischler, The impact of artificial intelligence on project management employees, 2024.
- 51 N.G. Castellanos, et al., Augmenting human judgment in AI-powered project management: A framework for collaborative decision-making, *J. Adv. Comput. Syst.* 2 (2) (2022) 10–16.
- 52 R. Linzalone, A. Bassi, A.M. Felicetti, S. Ammirato, Biases in modern project

- management. Opportunities connected to artificial intelligence (AI), in: Tomorrow's Data Empowered Project Management: Agile Decision Making, Sustainability and AI, Springer, 2025, pp. 199–220.
- 53 S. Haghsheno, AI-driven project management in software engineering, *Int. J. Sci. Dev. Res.* 6 (1) (2021) 299–308.
- 54 M. Jariwala, The impact of AI and data analytics on project management information systems (PMIS), in: *Project Management Information Systems: Empowering Decision Making and Execution*, IGI Global, 2025, pp. 117–160.
- 55 B. Haidabrus, Generative AI in agile, project, and delivery management, in: *Design, Simulation, Manufacturing: The Innovation Exchange*, Springer, 2024, pp. 100–110.
- 56 L.M. Amugongo, A. Kriebitz, A. Boch, C. Lütge, Operationalising AI ethics through the agile software development lifecycle: A case study of AI-enabled mobile health applications, *AI Ethics* (2023) 1–18.
- 57 M.R. Islam, et al., Navigating the digital landscape: Integrating advanced IT solutions with project management best practices, *ICRRD J.* 5 (4) (2024) 159–173.
- 58 M. Pourmojahed, P. Rahat, Adopting and implementing AI in organizations: A review from a project management perspective, 2024.
- 59 P. Diebold, From backlogs to bots: Generative AI's impact on agile role evolution, *J. Softw. Evol. Process* 37 (1) (2025) e2740.
- 60 J.C. Weng, Putting intellectual robots to work: Implementing generative AI tools in project management, NYU SPS Appl. Analytics Lab., 2023.
- 61 K. Sainio, Generative artificial intelligence assisting in agile project pain points, Master's Thesis, Tampere University, Finland, 2023.
- 62 H. Chen, B. Xu, K. Zhong, Enhancing software effort estimation through reinforcement learning-based project management-oriented feature selection, *arXiv preprint arXiv:2403.16749*, 2024.
- 63 X. Wang, S. Lu, X. Qian, C. Hu, X. Liu, Dynamic scheduling of decentralized high-end equipment R&D projects via deep reinforcement learning, *Comput. Ind. Eng.* 190 (2024) 110018.
- 64 S. Xiaoning, M. Mingjian, S. Ruyi, S. Liyan, Large-scale agile software project scheduling based on deep reinforcement learning, *J. Zhengzhou Univ. Eng. Sci.* 44 (5) (2023).
- 65 F. Xu, H. Uszkoreit, Y. Du, W. Fan, D. Zhao, J. Zhu, Explainable AI: A brief survey on history, research areas, approaches and challenges, in: *Natural Language Processing and Chinese Computing: 8th CCF Int. Conf. NLPCC 2019, Dunhuang, China, Oct. 9–14, 2019, Proceedings, Part II* 8, Springer, 2019, pp. 563–574.
- 66 K.W. De Bock, et al., Explainable AI for operational research: A defining framework, methods, applications, and a research agenda, *Eur. J. Oper. Res.* 317 (2) (2024) 249–272.
- 67 A. Abusitta, M.Q. Li, B.C. Fung, Survey on explainable AI: Techniques, challenges and open issues, *Expert Syst. Appl.* 255 (2024) 124710.
- 68 K. Koc, Role of Shapley additive explanations and resampling algorithms for contract failure prediction of public–private partnership projects, *J. Manag. Eng.* 39 (5) (2023) 04023031.
- 69 M.T. Ribeiro, S. Singh, C. Guestrin, "Why should I trust you?" Explaining the predictions of any classifier, in: *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2016, pp. 1135–1144.
- 70 E.E. Başakın, P.C. Stoy, M.C. Demirel, M. Ozdogan, J.A. Otkin, Combined drought index using high-resolution hydrological models and explainable artificial intelligence techniques in Türkiye, *Remote Sens.* 16 (20) (2024) 3799.

- 71 L.M. Encarnação, J. Kohlhammer, C.A. Steed, Visualization for AI explainability, *IEEE Comput. Graph. Appl.* 42 (6) (2022) 9–10.
- 72 N. Rane, Integrating leading-edge artificial intelligence (AI), internet of things (IOT), and big data technologies for smart and sustainable architecture, engineering and construction (AEC) industry: Challenges and future directions, *Eng. Constr. Ind. Challenges Future Directions* (2023).
- 73 S. Caldwell, et al., An agile new research framework for hybrid human-AI teaming: Trust, transparency, and transferability, *ACM Trans. Interact. Intell. Syst.* 12 (3) (2022) 1–36.
- 74 B. Cabrero-Daniel, T. Herda, V. Pichler, M. Eder, Exploring human-AI collaboration in agile: Customised LLM meeting assistants, in: *Int. Conf. Agile Softw. Dev.*, Springer Nature Switzerland Cham, 2024, pp. 163–178.
- 75 H.L. Lumbanraja, T. Raharjo, A.N. Fitriani, Artificial intelligence implementation in agile project management addressing challenges and maximizing impact, *Indones. J. Comput. Sci.* 13 (4) (2024).
- 76 A. Tak, S. Chahal, Risk management in agile AI/ML projects: Identifying and mitigating data and model risks, *J. Technol. Syst.* 6 (3) (2024) 1–18.
- 77 B. Akhiwu, Agile software development project management and integrations incorporating AI, *ResearchGate*, 2025. Available: <https://www.researchgate.net/publication/389548946>.
- 78 R. Moraga-Díaz, A. Leiva-Araos, J. García, A robust statistical methodology for measuring enterprise agility, *Appl. Sci.* 13 (14) (2023) 8445.
- 79 A. Bahi, J. Gharib, Y. Gahi, Integrating generative AI for advancing agile software development and mitigating project management challenges, *Int. J. Adv. Comput. Sci. Appl.* 15 (3) (2024) <https://doi.org/10.14569/ijacsa.2024.0150306>.
- 80 A. Dugbartey, O. Kehinde, Optimizing project delivery through agile methodologies: Balancing speed, collaboration and stakeholder engagement, *World J. Adv. Res. Rev.* 25 (1) (2025) 1237–1257. <https://doi.org/10.30574/wjarr.2025.25.1.0193>.
- 81 C. M. Olsson and N. L. Russo, “Applying Adaptive Structuration Theory to the Study of Context-Aware Applications,” in *Information Systems Research: Relevant Theory and Informed Practice*, B. Kaplan, D. P. Truex, D. Wastell, A. T. Wood-Harper, and J. I. DeGross, Eds., Boston, MA: Springer US, 2004, pp. 735–741. doi: 10.1007/1-4020-8095-6_51.
- 82 S. Cavusgil and S. Deligonul, “Dynamic capabilities framework and its transformative contributions,” *J. Int. Bus. Stud.*, vol. 56, Nov. 2024, doi: 10.1057/s41267-024-00758-8.
- 83 E. Deitrick, R. Shapiro, M. Ahrens, R. Fiebrink, P. Lehrman, and S. Farooq, Using Distributed Cognition Theory to Analyze Collaborative Computer Science Learning. 2015, p. 60. doi: 10.1145/2787622.2787715.
- 84 A. Macleod et al., “Sociomateriality: A Theoretical Framework for Studying Distributed Medical Education,” *Acad. Med. J. Assoc. Am. Med. Coll.*, vol. 90, Mar. 2015, doi: 10.1097/ACM.0000000000000708.
- 85 Y. Kaya, “Agile Leadership from the Perspective of Dynamic Capabilities and Creating Value,” *Sustainability*, vol. 15, no. 21, 2023, doi: 10.3390/su152115253.
- 86 A. Odeh, N. Odeh, and A. S. Mohammed, “A Comparative Review of AI Techniques for Automated Code Generation in Software Development: Advancements, Challenges, and Future Directions,” *TEM J.*, vol. 13, no. 1, pp. 726–739, 2024, doi: 10.18421/TEM131-76.