When AI Helps, When It Hurts: A Contextual Research Framework for Integrating Artificial Intelligence into Agile Scrum Workflows

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Abstract

As artificial intelligence (AI) increasingly enters agile project management environments, its impact remains inconsistent, boosting efficiency in some cases while disrupting collaboration in others. Rather than assuming AI's universal benefit, existing literature challenges this assumption and opens a knowledge gap for investigating the organizational and team-level conditions that moderate AI effectiveness. This paper conducts a literature review and proposes a research framework based on the constructs for the contextual analysis of AI in Agile Scrum, exploring when, how, and for whom AI integration enhances or hinders Agile Scrum workflows. It proposes a methodology for future research that is a quantitative-dominant mixed-methods approach, combining semi-structured interviews with a structured survey. The aim of this paper is to identify the contextual factors that shape AI's impact in Agile Scrum, which will serve as the basis for the research framework.

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Introduction

Artificial Intelligence (AI) has emerged as a key driver in modern project management (PM), enabling data-driven decision-making, predictive analytics, and process automation. (Tominc et al., 2023; Vergara et al., 2025). Considering AI has become a large, multidisciplinary area (Kaur et al., 2023)This paper will focus on the contextual integration of AI into project workflows, particularly within Agile methodologies, which represents a growing area of academic and practical interest (Koudriachov et al., 2025; Morales, 2024; Zadeh et al., 2024).

The paper assesses the impact of AI on Agile Scrum, a dominant Agile workflow within development teams. (Yusuf, 2025). Agile Scrum is an iterative project management workflow where work occurs in time-boxed 'sprints' (typically 2-4 weeks), guided by roles (Scrum Master, Product Owner), ceremonies (planning, daily stand-ups, retrospectives), and artifacts (product backlog, sprint backlog). While some researchers confirm that AI can enhance ceremonies and artifacts of Agile Scrum (Adamantiadou & Tsironis, 2025; Bahi et al., 2024; Kwasek et al., 2024)Others experience problems with limited accuracy, internal organizational support, and performance collapse in high-complexity tasks (Bengel, 2020; Morales, 2024; Shojaee et al., 2025). These inconsistencies suggest AI's impact is context-dependent and does not always help. The application of AI in agile frameworks remains underexplored, with limited empirical data on its practical implications. (Davenport & Ronanki, 2018). Crucially, human-centric factors, such as team expertise and morale, remain critical determinants of project outcomes even in AI-augmented environments. For instance, recent predictive modeling of agile projects identifies "team expertise score" and "team morale" as top features influencing success, underscoring that team capabilities precede technological efficacy. (Nejad et al., 2025). This reinforces the need to examine how organizational and team-level contextual factors moderate AI's impact. Therefore, we aim to uncover when, how, and for whom AI integration is effective in Agile Scrum workflows.

Rather than assuming universal benefits, we investigate conditions influenced by contextual factors that result in benefits and risks to the improvement or hindrance of Agile Scrum workflows. This supports a deeper understanding of how AI interacts with the human-centric principles of Agile Scrum. The three main objectives are: (1) to identify a research gap related to AI integration in Agile workflows, (2) to define a sufficient research framework that can address the identified gap, and (3) to identify contextual factors shaping AI's impact in Agile Scrum.

The remainder of this paper begins with a review of the existing literature, highlighting key gaps in understanding AI's impact on Agile Scrum workflows. Next, we introduce a research framework designed to examine when, how, and for whom AI integration enhances or impairs these workflows. We conclude by outlining the study's implications and proposing directions for future research.

Background and Related Work

The Agile Scrum workflows emphasize decentralized decision-making, team empowerment, and transparency (Koudriachov et al., 2025). It is increasingly employed across the IT sector to support rapid, iterative development and the continuous delivery of user value, as seen in the adoption of Scrum within mobile banking application teams aiming to accelerate feature releases and integrate user feedback more efficiently (Yusuf, 2025). Although 52% of Agile teams use Agile to reduce time-to-market, improve operational efficiency, and enhance responsiveness to change, 47% of Agile projects encounter inefficiencies due to numerous manual, human-centric activities, resulting in inaccurate timelines, budget challenges, and/or team misalignments (Widodo & Voutama, 2025). These challenges align with AI's capabilities, which are often cited as the primary factor shaping the 4.0 industrial revolution, contributing significantly to efficiency gains and advanced automation (Malik et al., 2024).

When AI tools are introduced to Agile workflows, they may enhance or disrupt the dynamics. A mere evaluation of the tools' output, such as that from Alliata et al. (2025), is insufficient for understanding the risks and benefits. Other studies go into more detail with the use of machine learning (ML) for sprint velocity forecasting, natural language processing (NLP) for user story refinement, and AI-powered assistants for task documentation. (Bala et al., 2025; Morales, 2024; Ulfsnes et al., 2025). One direction is the use of AI-based decision support systems, which have been shown to enhance Agile project management by enabling proactive risk mitigation and optimized resource allocation. As Almalki (2025) Emphasizes, these systems improve decision efficiency while promoting AI-driven methodologies that align with the adaptive nature of Agile workflows. These already contribute to a better understanding of the "how". However, adoption outcomes differ across organizational contexts, influenced by leadership involvement, team digital literacy, and infrastructure. (Bahi et al., 2024; Bengel, 2020). Ionașcu (2025) and Wörner (2023) highlight the differences in AI adoption across European Union countries, where we observe significant variations in general AI usage, illustrating a conditional effect. All the contextual variations underscore a fundamental tension: as observed in behavioral science, AI integration represents 'both an opportunity and a challenge' whose success hinges not only on technical capabilities but on "preserving a human-centered, ethically grounded approach." (Vascelli, 2025). This resonates powerfully in Agile Scrum workflows, where AI tools risk undermining core values, such as team autonomy and transparency, particularly during ceremonies like retrospectives, if implemented without proper ethical safeguards. (Jennings & Cox, 2024). Another valuable research from Kwasek et al. (2024) Depicted different perceptions toward the usage of AI to support organizational management by surveying 956 participants. However, the target sample was students, which may have yielded theoretically grounded answers rather than the practical experiences that management professionals would offer. Therefore, this paper highlights the need for evidence-based insights into the evolving intersection of AI and Agile workflows, as recommended by Vicci (2024).

The analysed literature seems to reveal a scarcity of empirical studies and real-world data. (Adamantiadou & Tsironis, 2025; Koudriachov et al., 2025; Nejad et al., 2025; Ulfsnes et al., 2025). Furthermore, there is a limited exploration of AI capabilities across Agile Scrum workflows (Morales, 2024). Specific AI applications, such as automated risk indicator retrieval, also remain largely unaddressed. (Adamantiadou & Tsironis, 2025; Koudriachov et al., 2025). The literature often neglects ethical considerations, including data privacy, algorithmic bias, and the evolving human-AI collaboration dynamics (Jennings & Cox, 2024; Ulfsnes et al., 2025). There is also a recognized need to investigate regional differences in AI adoption, particularly within the European context, to inform differentiated policies. (Ionașcu, 2025; Wörner, 2023). Addressing these gaps is vital for advancing the practical and responsible integration of AI in PM.

Additionally, the relevance of exploring the impact of AI in PM (in which Agile Scrum is a dominant workflow) is shown by the annual increase in the number of related publications, which was measured to have grown by 70% from 2019 to 2024 (Daraojimba et al., 2024; Vergara et al., 2025). Bengel (2020) further reconfirms that the popularity of the topic has risen since 2018. In 2025, some studies, such as the one led by Shojaee et al. (2025) from Apple's research team, began to challenge the usefulness of AI for more complex tasks. However, few existing studies rarely address non-linear or conditional effects and potential challenges.

Given the above, it remains unclear how, why, and under what conditions AI impacts Agile Scrum workflows positively or negatively, which is precisely what this article seeks to clarify conceptually.

Materials and Methods

This section identifies constructs for the contextual analysis of AI in Agile Scrum, a methodological approach to testing its impact, as well as the sampling and analysis unit. These are the three building blocks of the research framework.

The constructs table (Table 1) is grounded in two established models: the Technology–Organization–Environment (TOE) framework, which explains technology adoption based on technological capabilities, organizational readiness, and environmental context. (Baker, 2012), and the Unified Theory of Acceptance and Use of Technology (UTAUT), which captures user-level adoption behaviour through constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003).

To explore the conditional dynamics of "when," "how," and "for whom" AI helps or hinders Agile performance, we ground our methodological design in the two theoretical models mentioned: the TOE framework and the UTAUT. These models serve as foundational lenses to identify the relevant constructs and variables that influence AI integration outcomes across technological, organizational, environmental, and user-level domains.

To support the mentioned goals, this study proposes the following exploratory research questions:

- **RQ1:** Which latent constructs and manifest variables derived from the TOE framework are most relevant for understanding the contextual conditions under which AI supports or hinders Agile Scrum workflows?
- **RQ2:** What individual-level factors, as conceptualized by the UTAUT, shape the perceived usefulness, ease of use, and intention to adopt AI tools in Agile Scrum workflows?

These questions are not aimed at testing predefined hypotheses but rather at uncovering the relevant contextual dimensions and user-level variables that define the success or failure of AI adoption in Agile Scrum. The answers to these questions will inform the structure of the proposed research model and form the foundation for future quantitative validation.

Theoretical Construct Identification

To answer the proposed research questions and construct a research framework, this study identifies constructs and variables across the TOE and UTAUT frameworks. These constructs serve as the foundation for future empirical testing of the contextual factors that influence AI's success or failure in Agile Scrum workflows.

Table 1 presents the identified constructs and their operational variables, derived from recent, high-quality academic sources. The TOE model provides the macro-level context, including the nature of the applied AI technologies, organizational maturity, and environmental readiness. In contrast, the UTAUT model incorporates individual-level beliefs and adoption factors, including perceived usefulness, ease of use, ethical perception, facilitating conditions, and social influence. Constructs for the AI maturity level and literacy use scales were validated in previous research (Nejad et al., 2025; Sallam et al., 2023), while others were our operationalizations.

This dual-framework approach enables a multidimensional understanding of AI integration that considers both structural and human factors, providing a robust theoretical foundation for developing a research instrument and diagnostic framework.

Table 1
Operationalization of Constructs from TOE and UTAUT Frameworks for Contextual Analysis of AI in Agile Scrum

Domain	Construct	Variable	Definition	Source
Technology (TOE)	AI Subfield	Applied Techno-logy	Specific AI technologies used (e.g. machine learning) mapped to Scrum task types (e.g. backlog grooming, sprint planning).	(Eurostat, 2025; Russel & Norvig, 2021)
	AI Usefulness in Agile Scrum Workflows	Task-AI Alignment	Degree to which a specific AI subfield is suitable for the task's complexity, novelty, and ambiguity (e.g. "Was AI useful for complex prioritization?").	(Davenport & Ronanki, 2018; Shojaee et al., 2025)
	AI Decision Support Capabilities	Decision Support System Functio-nality	Extent to which AI-powered decision support systems enhance Agile Scrum project efficiency through risk mitigation, adaptive planning, and optimized resource allocation.	(Almalki, 2025)
Organization (TOE)	Agile Maturity	Agile Maturity Level	Organization's maturity based on Agile Maturity Model.	(Sallam et al., 2023)
	Organizational Support for AI	AI Initiative Support	Financial, legal, decision, and policy-level organizational support (e.g. tool procurement, legal clearance, training budgets, decision making protocols).	(Almalki, 2025; Bengel, 2020; Eurostat, 2025)
	AI Literacy	Six-Dimensional AI Fluency Index	Self-report using Likert scale to assess fluency across 6 dimensions: Conceptual, Technical, Critical, Application, Collaboration, Ethical.	(Nejad et al., 2025; Ng et al., 2021)
	Regional Moderation	Country Cluster (AI Maturity)	Assigned per respondent based on country clusters.	(Eurostat, 2025)
User-Level (UTAUT)	Performance Expectancy	AI Usefulness Belief	Perceived usefulness of AI for Scrum tasks (e.g. better sprint planning, faster refinement).	(Morales, 2024)
	Effort Expectancy	Ease of Use	Perceived cognitive effort to use AI tools (prompting, integration, etc.).	(Alliata et al., 2025; Nejad et al., 2025)

	Social Influence	Team or Leader Pressure	Perceived pressure from peers or management to adopt AI tools.	(Kwasek et al., 2024)
	Ethical Perception	Trust in AI fairness	Perceived fairness and objectivity of AI outputs (e.g., "I trust AI-suggested sprint priorities").	
	Facilitating Conditions	Tooling & Infrastructure Support	Availability of tools, onboarding, documentation, technical support for AI.	(Morales, 2024; Ulfsnes et al., 2025)

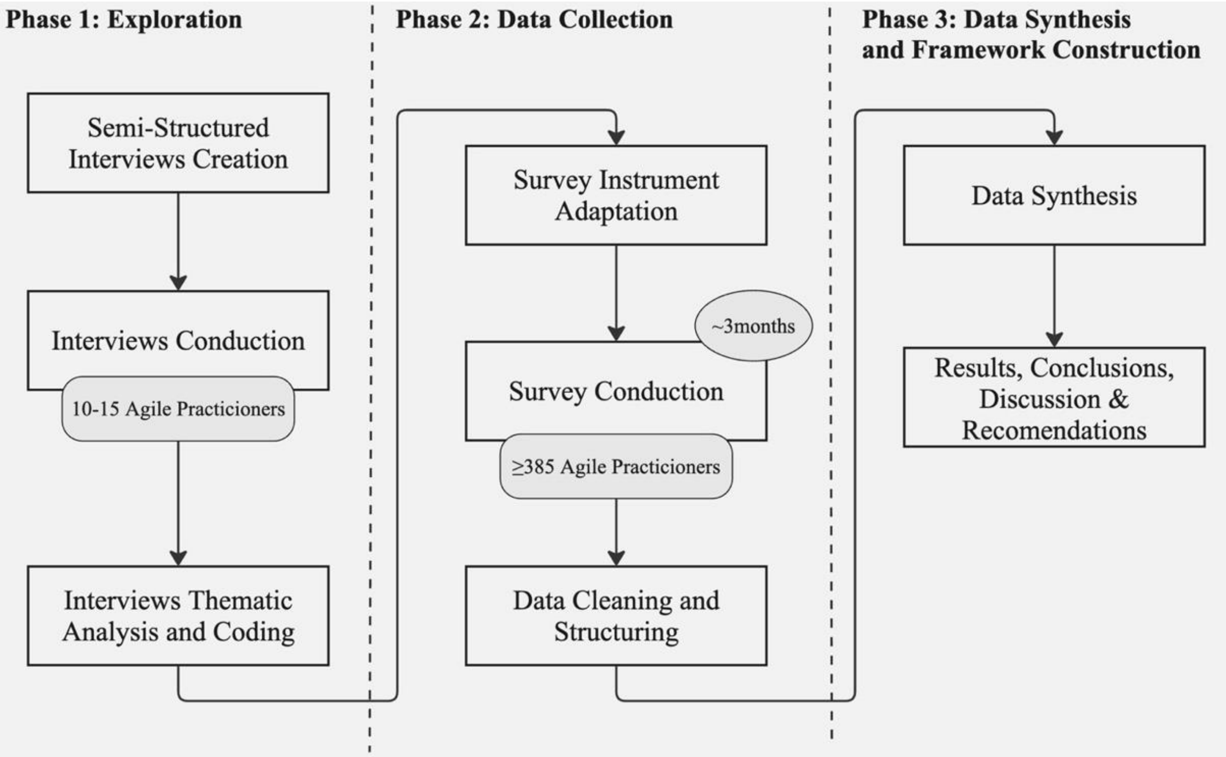
Source: Adapted from (Alliata et al., 2025; Almalki, 2025; Bengel, 2020; Davenport & Ronanki, 2018; Eurostat, 2025; Kwasek et al., 2024; Morales, 2024; Nejad et al., 2025; Ng et al., 2021; Russel & Norvig, 2021; Sallam et al., 2023; Shojaee et al., 2025; Ulfsnes et al., 2025).

The identified constructs and variables (Table 1) form the theoretical backbone of the proposed research design. To operationalize identified constructs, the study employs a three-phase research process, as illustrated in Figure 1. The process begins with qualitative exploration through semi-structured interviews to refine contextual factors. Insights from this phase inform the development and adaptation of a structured survey instrument, which is deployed at scale to validate the construction of a recommendation framework, a broader, still insufficiently defined, goal of future research.

This paper suggests a sequential mixed-methods design, structured across three distinct phases to address the research objectives. The approach begins with qualitative exploration to contextualize the research framework, transitions to quantitative validation through large-scale survey deployment, and culminates in integrative synthesis of findings. This sequential design ensures that exploratory insights from initial interviews systematically inform the instrument development and analytical framework for the subsequent quantitative phase.

As we suggest a multinational study, English is its operational language to address linguistic diversity across European participants. All research instruments (interview protocols, survey questionnaires), data collection procedures, analytical processes, and scholarly outputs should be conducted and presented in English. Participants should be required to demonstrate professional working proficiency in English during screening to mitigate cross-linguistic interpretation risks and maintain conceptual consistency throughout the research lifecycle.

Figure 1
Process of the Research Method



Source: Adapted from (Bryman et al., 2021; Creswell & Creswell, 2023; Zikmund et al., 2010).

Secondary data will provide further contextual grounding and support for primary findings. Sources will include:

- **AI-Specific Data**: Eurostat databases will offer organizational-level insights into AI adoption trends across industries, regions, and demographics. For example, the use of AI in enterprises (Eurostat, 2025).
- **Literature Review**: A thorough review of recent academic and industry publications will frame the study within existing knowledge and identify areas for further research.

Sampling and Analysis Unit

The initial exploratory phase involves conducting semi-structured interviews with 10–15 experienced Agile Scrum practitioners recruited through purposive and snowball sampling. Participants will include Project Managers, Scrum Masters, Product Owners, and development team members from diverse European organizations to capture heterogeneous perspectives on AI integration challenges. Data collection will use in-person or video-conferencing interviews (e.g., Google Meet) to accommodate participants' preferences and ensure flexibility. However, in-person interviews are preferred to capture nuances. Interviews will be audio-recorded, transcribed verbatim, and analysed through inductive thematic analysis. This process includes open coding of transcripts, iterative theme development, and constant comparative analysis to identify emergent patterns related to contextual factors influencing AI adoption. Findings from this phase will refine the operational definitions of constructs in Table 1 and inform adaptations to the survey instrument for Phase 2.

Building on qualitative insights, a structured survey instrument will be developed for Agile practitioners across the European Union. Respondents' countries will be mapped to pre-defined AI maturity clusters derived from Eurostat data using K-means clustering, operationalizing the regional moderation construct. A simple random sampling strategy will be used, followed by post-stratification to segment participants into AI users and non-users. This approach enables comparative analysis across adoption profiles. Data collection will be conducted via an online survey using tools such as Google Forms or SurveyMonkey. This method ensures wide accessibility, efficient distribution, and real-time data collection. The best tool will be chosen based on its ability to enable post-stratification. The survey will leverage multiple digital platforms and techniques to maximize reach and targeting precision. Distribution will primarily occur through professional networks such as LinkedIn and agile-specific forums, with a strong focus on IPMA (International Project Management Association) and PMI (Project Management Institute) groups. Additionally, email outreach will target individuals from PMI and IPMA databases, specifically those holding certifications in Agile Scrum and project management, ensuring a highly relevant participant pool that will hopefully be available for academic purposes. Following data collection, rigorous cleaning procedures will be implemented, including outlier detection, missing-value analysis, and consistency checks, to ensure data integrity before analysis. Final data will be analysed in JASP software to visualize results and drive further conclusions and hypothesis testing.

Given the vast, undefined population of individuals involved in agile workflows, a standard formula for estimating sample size in an infinite population will be used. (Zikmund et al., 2010):

$$n = \frac{Z^2 \times p \times (1-p)}{e^2}$$

Where:

n = required sample size
Z = Z-score corresponding to the desired confidence level (1.96 for 95% confidence)
p = estimated proportion of the population (0.5 used for maximum variability)
e = margin of error (0.05 for ±5%)

Substituting the values:

$$n = \frac{1.96^2 \times 0.5 \times (1-0.5)}{0.05^2} = \frac{3.8416 \times 0.25}{0.0025} = 384.16$$

Rounding up, the minimum required sample size is 385 respondents. This calculation ensures a 95% confidence level with a 5% margin of error, assuming maximum variability in responses.

In the final phase, quantitative data will undergo advanced statistical analysis, including exploratory factor analysis (EFA) to validate measurement structures, confirmatory factor analysis (CFA) to test psychometric properties, and structural equation modeling (SEM) to examine relationships between constructs.

Given the rapid pace of AI advancements, obtaining timely results is critical. To ensure the findings remain relevant, the entire survey process—from data collection to final reporting—will be timeboxed to a maximum of 18 months. This timeline aligns with Zikmund et al. (2010), who highlight the importance of addressing timeliness in rapidly evolving fields.

Ethical Considerations

Confidentiality and privacy will be strictly upheld throughout the research process, in accordance with ethical standards to protect participant data. By targeting specific and trusted groups, such as certified practitioners in agile and project management, bias and unreliable responses will be minimized.

Conclusion

This paper examines the conditional nature of AI's impact on Agile Scrum workflows and defines a research framework that can guide empirical investigation. To address this, two research questions were posed: to identify relevant constructs from the TOE and UTAUT frameworks and to integrate them into a coherent model for understanding when, how, and for whom AI helps or hinders Agile practices.

First, in response to RQ1, the study identified core constructs from the TOE framework that define the organizational and environmental conditions influencing AI adoption. These include applied AI subfields, task-AI alignment, agile maturity, organizational support, AI literacy, and regional readiness. These factors together shape the context in which AI either enables or disrupts Agile processes.

Second, to address RQ2, the UTAUT model was applied to surface key user-level variables that influence perceived usefulness and AI adoption in Agile teams. Specifically, performance expectancy, effort expectancy, social influence, and facilitating conditions were identified as critical to understanding how individuals engage with AI tools in their Scrum roles.

Based on these insights, the next step is to conduct the proposed empirical research process. This involves qualitative interviews to refine the contextual and individual-level constructs, followed by a structured survey to quantify and compare perceptions across AI users and non-users in Agile environments. The findings will help validate the relevance of the identified constructs and guide practitioners in tailoring AI adoption strategies to specific organizational and team conditions.

By addressing these two research questions, the study lays a conceptual foundation for the adoption of context-sensitive AI in Agile Scrum. It contributes to the literature by moving beyond generalized claims and offering a structured approach for future empirical inquiry.

References

1. Adamantiadou, D. S., & Tsironis, L. (2025). Leveraging Artificial Intelligence in Project Management: A Systematic Review of Applications, Challenges, and Future Directions. *Computers*, *14*(2), 66. https://doi.org/10.3390/computers14020066
2. Alliata, Z., Singhal, T., & Bozagiu, A.-M. (2025). The AI Scrum Master: Using Large Language Models (LLMs) to Automate Agile Project Management Tasks. In *Marchesi, L., et al. Agile Processes in Software Engineering and Extreme Programming – Workshops. XP 2024. Lecture Notes in Business Information Processing, vol 524. Springer, Cham* (pp. 110–122). https://doi.org/10.1007/978-3-031-72781-8_12
3. Almalki, S. S. (2025). AI-Driven Decision Support Systems in Agile Software Project Management: Enhancing Risk Mitigation and Resource Allocation. *Systems*, *13*(3), 208. https://doi.org/10.3390/systems13030208
4. Bahi, A., Gharib, J., & Gahi, Y. (2024). Integrating Generative AI for Advancing Agile Software Development and Mitigating Project Management Challenges. *International Journal of Advanced Computer Science and Applications*, *15*(3). https://doi.org/10.14569/IJACSA.2024.0150306
5. Baker, J. (2012). The Technology–Organization–Environment Framework. In *Dwivedi, Y., Wade, M., Schneberger, S. (eds) Information Systems Theory. Integrated Series in Information Systems, vol 28. Springer, New York, NY* (pp. 231–245). https://doi.org/10.1007/978-1-4419-6108-2_12
6. Bala, S., Sahling, K., Haase, J., & Mendling, J. (2025). ChatGPT for Tailoring Software Documentation for Managers and Developers. In *Marchesi, L., et al. Agile Processes in*

Software Engineering and Extreme Programming – Workshops. XP 2024. Lecture Notes in Business Information Processing, vol 524. Springer, Cham (pp. 103–109). https://doi.org/10.1007/978-3-031-72781-8_11
7. Bengel, D. (2020). *Organizational Acceptance of Artificial Intelligence*. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-30794-3
8. Bryman, A., Clark, T., Foster, L., & Sloan, L. (2021). *Social Research Methods* (6th ed.). Oxford University Press.
9. Creswell, J. W., & Creswell, J. D. (2023). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (6th ed.). SAGE Publications.
10. Daraojimba, E. C., Nwasike, C. N., Adegbite, A. O., Ezeigweneme, C. A., & Gidiagba, J. O. (2024). Comprehensive Review of Agile Methodologies in Project Management. *Computer Science & IT Research Journal*, *5*(1), 190–218. https://doi.org/10.51594/csitrj.v5i1.717
11. Davenport, T. H., & Ronanki, R. (2018, February). Artificial Intelligence for the Real World. *Harvard Business Review*. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world
12. Eurostat. (2025, July 22). *Use of Artificial Intelligence in Enterprises*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises
13. Ionașcu, C. M. (2025). Artificial Intelligence Adoption in the European Union: A Data-Driven Cluster Analysis (2021–2024). *Economies*, *13*(5). https://doi.org/10.3390/economies13050145
14. Jennings, A. M., & Cox, D. J. (2024). Starting the Conversation Around the Ethical Use of Artificial Intelligence in Applied Behavior Analysis. *Behavior Analysis in Practice*, *17*(1), 107–122. https://doi.org/10.1007/s40617-023-00868-z
15. Kaur, R., Gabrijelčič, D., & Klobučar, T. (2023). Artificial intelligence for cybersecurity: Literature review and future research directions. *Information Fusion*, *97*, 101804. https://doi.org/10.1016/j.inffus.2023.101804
16. Koudriachov, C., Tam, C., & Aparicio, M. (2025). Success with Agile Project Management: Looking back and into the future. *Journal of Systems and Software*, *226*, 112428. https://doi.org/10.1016/j.jss.2025.112428
17. Kwasek, A., Kocot, M., Kocot, D., Maciaszczyk, M., & Rogozinska-Mitrut, J. (2024). The Role of Artificial Intelligence in Agile Organization Management. *European Research Studies Journal*, *XXVII*(Issue 2), 118–130. https://doi.org/10.35808/ersj/3374
18. Malik, S., Muhammad, K., & Waheed, Y. (2024). Artificial Intelligence and Industrial Applications - A Revolution in Modern Industries. *Ain Shams Engineering Journal*, *15*(9), 102886. https://doi.org/10.1016/j.asej.2024.102886
19. Morales, M. C. (2024). *AI-powered Scrum: A systematic literature review of the current trends and the state-of-the-art of Artificial Intelligence capabilities in agile project management*. Stockholm University.
20. Nejad, A. A. F., Arabikhan, F., Gegov, A., Jafari, R., & Ichtev, A. (2025). Data-Driven Predictive Modelling of Agile Projects Using Explainable Artificial Intelligence. *Electronics*, *14*(13), 2609. https://doi.org/10.3390/electronics14132609
21. Ng, D. T. K., Leung, J. K. L., Chu, K. W. S., & Qiao, M. S. (2021). AI Literacy: Definition, Teaching, Evaluation and Ethical Issues. *Proceedings of the Association for Information Science and Technology*, *58*(1), 504–509. https://doi.org/10.1002/pra2.487
22. Russel, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson. ISBN-10: 0-13-461099-7
23. Sallam, S. H. A., Fouad, M. M., & Hemeida, F. (2023). Relationship between Agile Maturity and Digital Transformation Success. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *33*(3), 154–168. https://doi.org/10.37934/araset.33.3.154168
24. Shojaee, P., Mirzadeh, I., Alizadeh, K., Horton, M., Bengio, S., & Farajtabar, M. (2025). *The Illusion of Thinking: Understanding the Strengths and Limitations of Reasoning Models via the Lens of Problem Complexity*. https://doi.org/10.48550/arXiv.2506.06941
25. Tominc, P., Oreški, D., & Rožman, M. (2023). Artificial Intelligence and Agility-Based Model for Successful Project Implementation and Company Competitiveness. *Information*, *14*(6), 337. https://doi.org/10.3390/info14060337

26. Ulfsnes, R., Moe, N. B., Emmerhoff, J., Floryan, M., Griva, A., Gundelsby, J. H., Barbala, A. M., & Conboy, K. (2025). Responsible AI in Agile Software Engineering - An Industry Perspective. *In Marchesi, L., et al. Agile Processes in Software Engineering and Extreme Programming – Workshops. XP 2024. Lecture Notes in Business Information Processing, Vol 524. Springer*, 33–41. https://doi.org/10.1007/978-3-031-72781-8_4
27. Vascelli, L. (2025). From philosophy to algorithms: a commentary on the evolution of human behavior and the role of artificial intelligence. *Discover Artificial Intelligence*, *5*(1), 138. https://doi.org/10.1007/s44163-025-00394-7
28. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540
29. Vergara, D., del Bosque, A., Lampropoulos, G., & Fernández-Arias, P. (2025). Trends and Applications of Artificial Intelligence in Project Management. *Electronics*, *14*(4), 800. https://doi.org/10.3390/electronics14040800
30. Vicci, H. (2024). *The Power of Artificial Intelligence in Project Management: A Review and Evaluation Study* (pp. 12–14). College of Business Florida International University. https://doi.org/10.2139/ssrn.4834838
31. Widodo, D. A. P., & Voutama, A. (2025). Generative Artificial Intelligence in Agile Product Management: Optimizing Task Coordination and Team Efficiency in Software Development. *The Indonesian Journal of Computer Science*, *14*(3). https://doi.org/10.33022/ijcs.v14i3.4800
32. Wörner, T. (2023). *The Dynamics of Artificial Intelligence in Europe: Investigating the Adoption and Impact on Business Performance and Sectorial Transformation in the Construction Industry*. Nova School of Business and Economics. Accessed at http://hdl.handle.net/10362/173229 on July 18, 2025.
33. Yusuf, A. A. (2025). Evaluation of Scrum Implementation Maturity Level based on Scrum Body of Knowledge. *The Indonesian Journal of Computer Science*, *14*(1). https://doi.org/10.33022/ijcs.v14i1.4619
34. Zadeh, E. K., Khoulenjani, A. B., & Safaei, M. (2024). Integrating AI for Agile Project Management: Innovations, Challenges, and Benefits. *International Journal of Industrial Engineering and Construction Management*, *1*(1), 1–10.
35. Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2010). *Business Research Methods (pp. 386-459)* (8th Edition). South Western Cengage Learning.

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