International Journal of
Technology and Systems
(IJTS)

Risk Management in Agile Al/Ml Projects: Identifying and Mitigating Data and Model Risks

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024
www.carijournals.org

Risk Management in Agile Al/Ml Projects: Identifying and Mitigating Data and Model Risks

Ankur Tak, Sunil Chahal

https://orcid.org/0009-0005-8548-1636

Accepted: 20th Mar, 2024 Received in Revised Form: 5th Apr, 2024 Published: 22nd Apr, 2024

Abstract

Purpose: This study addresses the crucial challenge of managing risks associated with data and models in Agile Artificial Intelligence (AI) and Machine Learning (ML) projects. It aims to develop a systematic framework for effective risk control utilizing agile methodologies.

Methodology: The research is grounded in an interpretivist approach and utilizes a deductive method. It constructs a comprehensive framework for identifying and mitigating risks, integrating risk management seamlessly into Agile processes for AI and ML development.

Findings: The study introduces four technological themes critical for risk mitigation: dynamic distribution of resources, model robustness, risk integration, and quality assessment of information. These themes provide actionable strategies for reducing risks throughout the Agile AI/ML development lifecycle, ensuring that risk assessment and mitigation are integral to project planning and execution.

Unique contribution to theory, practice, and policy: The study contributes to both theory and practice by offering a detailed, actionable framework for risk management in Agile AI/ML projects. It advocates for the adoption of adaptive technologies and tools, continuous stakeholder engagement, and adherence to ethical standards. Recommendations include validation of the framework through empirical research and ongoing longitudinal evaluations to adapt and refine risk management practices. This approach aims to enhance the reliability and efficiency of project outputs in dynamic environments, providing a significant foundation for policy development in technology project management.

Keywords: *Machine Learning, Risk Perceptions, Management Tactics, Circumstances, Conference Proceedings*

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024
www.carijournals.org

INTRODUCTION

1.1 Research background

The convergence of Agile techniques and Artificial Intelligence (AI), as well as Machine Learning (ML) programs, has arisen as a lively field of research and practice in recent years. Agile approaches have gained popularity for their responsiveness to rapidly changing project needs due to their iterative as well as incremental methods for the creation of software [1]. However, incorporating AI and machine learning into Agile workflows creates a new set of issues, particularly in the areas of the quality of data, accuracy of models, and comprehension. Information-related risks include data bias, inconsistency, and issues with confidentiality, all of which can have a substantial impact on the trustworthiness of AI/ML models. Framework-related hazards on the other hand, include difficulties in selecting a model, hyperparameter adjustment, and complex framework interpretability [2]. These hazards are significant impediments to getting the required results in AI/ML initiatives within a framework of Agile. This study intends to look into the essential subject of risk control within Agile AI/ML initiatives, with a particular emphasis on detecting and managing data and model concerns [3]. Practitioners as well as stakeholders can improve the accomplishment rate and efficacy of AI/ML projects in Agile contexts by knowing and addressing these issues.

1.2 Research aim and objectives

***Research Aim*:**

This study aims to improve the success and efficacy of Agile AI/ML initiatives by creating a thorough methodology for recognizing and minimizing data and modelling risks.

***Objectives*:**

- To investigate the effect of data-related hazards on the effectiveness and dependability of AI/ML models in Agile contexts.
- Identify and evaluate existing risk control tactics and procedures in Agile AI/ML initiatives focusing on data quality and model clarity.
- To create a solid foundation for proactive risk assessment and mitigation in Agile AI/ML initiatives.
- To provide guidelines along with best practices for smoothly integrating procedures for risk administration into Agile workflows, assuring the maximum efficiency of AI/ML models during the course of the project lifecycle.

1.3: Research Rationale

This study was motivated by the need to manage the inherent challenges and unknowns in Agile AI/ML initiatives. Integrating AI/ML into Agile frameworks has distinct problems, especially in terms of data quality as well as the accuracy of models [4]. Inadequately managing

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024
www.carijournals.org

data as well as model risks might result in unsatisfactory results and a failed project. By offering a methodical way to identifying and mitigating these hazards, this study attempts to fill a critical gap in existing research [5]. By doing so, it hopes to provide stakeholders and practitioners with the understanding and resources they need to manage the complexities of Agile AI/ML initiatives, enhancing their chances of success.

LITERATURE REVIEW

2.1: Agile Methodology in AI/ML Projects

Agile technique, which was originally designed for software development, is increasingly being used in Artificial Intelligence (AI) along with Machine Learning (ML) projects. It is distinguished by its incremental, collaborative, and adaptable managing projects approach [6]. Agile concepts stress adaptability to changing data countryside, changing model needs, and the requirement for continual development in the larger context of machine learning and AI. The development approach in Agility AI/ML projects is separated into tiny, manageable increments known as sprints [7]. These sprints usually run between one and four weeks and result in a product being delivered, which could be a functioning component within the AI/ML system as well, an updated framework, or improved data pretreatment techniques. This incremental strategy enables teams to respond quickly to developing obstacles and opportunities by allowing for rapid feedback channels [8]. Furthermore, Agile promotes cross-functional collaboration among data scientists, technicians, and domain specialists.

Fig. 2.1.1: Agile Methodology in AI/ML

Due to the multifaceted nature of AI/ML research, this collaborative atmosphere supports effective communication, information sharing, and collectively solving issues. AI/ML projects that use Agile approaches gain a capacity to adapt to changing requirements, embrace new data sources, as well as iteratively optimize models [9]. This iterative process yields more resilient, accurate, and operational AI/ML solutions in the end.

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024
www.carijournals.org

2.2: Data-Related Risks in Agile AI/ML Projects

Data-related hazards are an important aspect of Agility Artificial Intelligence (AI) as well as Machine Learning (ML) initiatives that must be carefully monitored. These hazards are primarily related to the data effectiveness, integrity, and applicability utilized to train and evaluate models using machine learning and AI [10]. Data biases caused by skewed or not representative information might result in models producing inaccurate or unjust results, particularly in sensitive areas such as healthcare or finance. Inconsistencies in the data as well as incompleteness can stymie the training manipulation, resulting in systems that fail to be generalized successfully [11]. Concerns about privacy also loom big, particularly in initiatives involving sensitive or personally identifying data. The importance of regulatory compliance as well as ethical considerations cannot be overstated [12]. Furthermore, the constantly changing character of Agile endeavors may provide issues in sustaining the accuracy of data over time, particularly as fresh sources of information are added or requirements change.

Fig. 2.2.1: Machine Learning Project

These dangers need constant monitoring, confirmation, and, if possible, the construction of systems to correct data-related concerns in real-time [13]. Addressing data-related dangers in Agile AI/ML initiatives requires a mix of strong data preprocessing, continual surveillance, and adherence to information management best practices [14]. To ensure the reliability and honesty of AI/ML models inside the Agile framework, defined standards for data gathering, validation, and ongoing upkeep must be established.

2.3: Model-Related Risks in Agile AI/ML Projects

Modeling-related risks within Agile Artificial Intelligence (also called AI) include issues with ML model choosing, development, and then deployment [15]. These dangers stem from the complexities of model building and the necessity for iterative improvement in Agile workflows. One big risk is the choice of models, where selecting the wrong algorithm or architecture might

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024

result in inferior performance [16]. Furthermore, hyperparameter tuning, an important step in increasing the efficiency of models, can to accomplished efficiently within the time restrictions of Agile sprints [17]. Another danger is the interpretability of complicated models, particularly in circumstances where explain ability is crucial for complying with regulations or customer understanding.

Fig. 2.3.1: Agile AI/ML Projects

Furthermore, when the fundamental data distribution changes, model erosion or drift can occur. With a concentration on adaptability, agile endeavors must cope with the requirement to regularly track and revise models in order to retain their efficacy [18]. To address modeling-related risks in Rapid AI/ML projects, a combination of cautious model selection, thorough verification and testing, and the inclusion of feedback mechanisms for continuous development is required [19]. In order to guarantee the reliability and confidence of AI/ML solutions, strategies for model comprehension and robustness ought to be incorporated into the creation process.

2.4: Existing Risk Management Strategies in Agile AI/ML Projects

Existing risk management solutions in Rapid Artificial Intelligence (AI) managing Machine Learning (ML) programs include a variety of practices for recognizing, evaluating, and reducing possible risks throughout the project lifetime [20]. One common strategy is to do extensive evaluations of risks at the start of the project. This entails a thorough examination of data sources, and possible biases, including model complications [21]. To prioritize and resolve identified hazards, risk matrices as well as probability-impact estimations are frequently used. Agile approaches include continuous surveillance and feedback loops. Teams put in place procedures to monitor the model's efficiency, data quality, as well emerging threats [22]. Regular retrospectives as well as sprint reviews allow teams to reflect on difficulties and alter strategies as needed [23].

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024
www.carijournals.org

Additionally, using a test-driven design (TDD) strategy might assist in spotting and resolving hazards early in the design process.

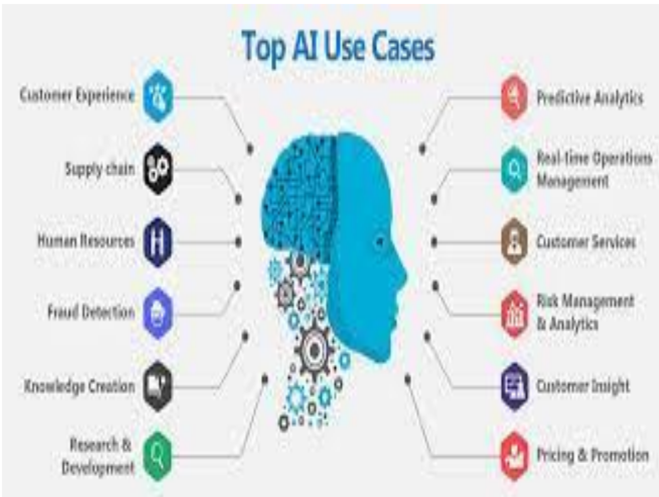

Fig. 2.4.1: AI for Risk Management

Teams can identify possible problems before they become more serious by developing tests that validate particular aspects of the information and model behavior. Risk management relies heavily on teams of professionals and collaboration [24]. Incorporating domain experts, statisticians, and engineers within evaluating risks and mitigation measures in Agile AI/ML initiatives ensures an exhaustive strategy [25]. Overall, these techniques help build a strong risk management framework for Agile AI/ML projects, empowering teams to take proactive measures to overcome obstacles and raise the likelihood regarding successful project completion.

2.5: Literature Gap

The present literature on handling hazards in Scrum AI/ML projects mainly concentrates on conventional programming or generic Agile methods. There is, however, a large research void that especially addresses the difficulties and tactics needed for successfully managing information as well as model risks in Agile AI/ML scenarios. By offering a customized framework adapted to the complexities of AI/ML programs within a Rapid framework, our research seeks to close this gap.

METHODOLOGY

This study is guided by interpretivism, which emphasizes the need to comprehend the varying perspectives as well as experiences of those involved in Agility AI/ML initiatives. This method recognizes that risk perceptions and management tactics depend on the circumstances and are impacted by individual viewpoints within the complex project environment [26]. The research method is directed by an approach known as deductive. This involves developing precise hypotheses and verifiable assertions from accepted theories, and models, including prior information [27]. Deductive reasoning is consistent with the goal of creating a formal framework for detecting and minimizing data and model vulnerabilities in Agile AI/ML initiatives. To comprehensively record and examine the present scenario of risk administration techniques within Agility AI/ML initiatives, a descriptive study design is used [28]. This approach makes it possible to examine data and analyze hazards in-depth, giving a clear picture of current tactics and their efficacy. In order to gather pertinent data, secondary data collecting is done from already published academic literature, investigations, reports on projects, and company whitepapers [29]. This includes recognized internet repositories, academic publications, and conference proceedings. The emphasis is on peer-reviewed literature that provides perceptions on risk management procedures, difficulties, and answers in Agile AI/ML initiatives [30]. Conduct a thorough analysis of academic papers, and books, including reports on agile development, AI/ML initiatives, and risk management tactics. To manage data as well as model hazards in Agile contexts, identify essential ideas, mathematical models, and optimal procedures [31]. Create a conceptual framework that includes the risk factors that have been identified, mitigation techniques, and methods for agile development. Using theoretical foundations and discovered holes in the literature, derive concrete hypotheses [32]. Create testable hypotheses about the efficiency of various risk management strategies within Agile AI/ML programs. employing cutting-edge analytics methods like content analysis and theme coding to identify crucial patterns, trends, and insights in relation to risk management strategies [33]. The conceptual framework will be iteratively improved depending on new discoveries to ensure its applicability and thoroughness. Validation of the created framework through expert discussions and polls to get opinions on its relevance as well as practical usefulness [34]. Technical aspects, such as data-driven measurements and statistical analysis, must be included into a coherent, practical framework in order to manage data and model risks in Agile AI/ML initiatives.

RESULTS

4.1 Risk Assessment and Mitigation Strategies for Data Quality in Agile AI/ML Projects

Any AI/ML project must have high-quality data to succeed, and this difficulty is made even more difficult in Agile settings where quick iterations and changing needs are the norms [35]. This technical theme explores the creation of efficient risk evaluation and mitigation techniques that are specifically intended to improve data quality inside Agile AI/ML initiatives.

***Technical Focus*:**

The systematic assessment and improvement of the quality of information through the Agile method of development is the technological focus [36]. This includes techniques for detecting data biases, managing missing or imperfect data, and reducing noise or outliers.

***Innovation Aspect*:**

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024

Cutting-edge methods include automated data cleansing and validation processes right into Agile workflows [37]. This could involve the use of sophisticated outlier detection computations, the correction of missing numbers, and methods to spot and fix biases.

Fig. 4.1.1: AI for Project Manager

***Measurement and Validation*:**

The theme places a strong emphasis on developing measurements and validation processes to evaluate changes in data quality in a quantitative manner [38]. This could include metrics pertaining to completeness of data and representation, or measurements like precision, reliability, and recollection for categorization jobs.

***Dynamic Data Profiling*:**

Agile AI/ML projects may see a rapid evolution of the data landscape. In order to enable the ongoing monitoring of information quality metrics, methods for dynamic data characterization are developed [39]. This makes it possible to quickly identify and address new data quality problems.

***Feedback-Driven Iterations*:**

Agile concepts are combined with risk mitigation measures to promote a feedback-driven method for improving data quality [40]. Teams can modify their data collecting and preprocessing processes via continuous feedback loops in response to insights acquired from the model's success and changing demands of the project.

4.2 Model Robustness and Explain ability in Agile AI/ML Workflows

Making sure that models are not just accurate but also reliable and understandable is of the utmost significance in Agile AI/ML workflows. This technological theme focuses on the creation of methods and tactics to strengthen the resistance of AI/ML models to adversarial attacks or modifications in data distributions, as well as the facilitation of model interpretation for stakeholders throughout the Agile framework [41].

***Robustness*:**

Model robustness is the capacity of a model developed using machine learning to sustain its efficacy and dependability in difficult circumstances, such as when it comes into contact with data that it has never seen before or experiences purposeful attempts to deceive it (adversarial attacks) [42]. It's critical to create models that are able to adapt and function consistently in Scrum workflows when needs and data might change quickly.

***Innovation Aspect*:**

Adversarial training, in which models are purposefully exposed to adversarial cases during training to strengthen their robustness, is one example of an innovative approach [43]. Models can generalize successfully to fresh information distributions by using approaches like domain adaption or transfer learning, among others.

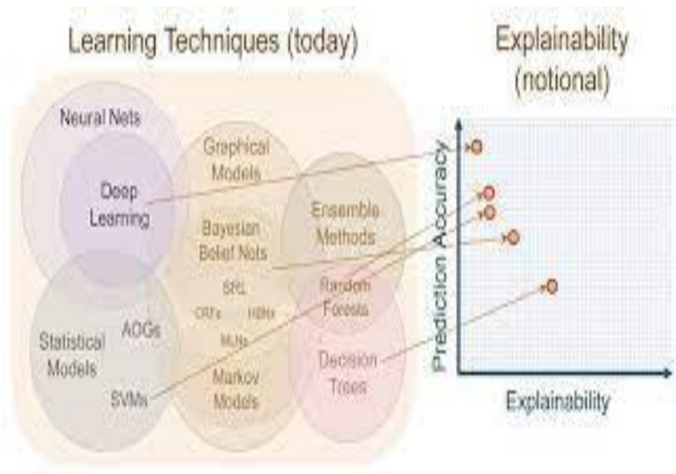

Fig. 4.2.1: Case for Explain ability in Agile AI

***Explain ability*:**

Model explainability aims to increase transparency and comprehension of AI/ML models among stakeholders, especially those who might not have a background in technology. Gaining confidence and achieving regulatory compliance depends on this [44]. The ability to explain becomes much more important in Agile since collaboration, as well as communication, are key components.

***Innovation Aspect*:**

Here, new methods are developed to produce interpretable justifications for model predictions, including the LIME algorithm (Local Interpretable Modelling-agnostic Explanations) and SHAP (Shapley Augmented Explanations) [45]. The advancement of visualizing tools and methods can also help to simplify the explanation of complex behavioral models.

4.3 Integration of Risk Management Processes into Agile Frameworks

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024

Agile frameworks must include risk management if AI/ML projects are to be completed successfully. The creation of standards and technologies to seamlessly integrate risk identification, examination, and mitigation activities into agile design cycles is the focus of this scientific theme [46].

***Synchronized Iterations*:**

Sprints are the short, iterative cycles used in agile development. Each sprint should have time set aside to determine potential risks, analyzing their implications, and formulating mitigation plans in order to integrate risk management [47]. By doing this, risk management is ensured to become an integral part of the design process.

***Risk Prioritization and Backlog Management*:**

Agile projects keep a backlog of improvements and tasks. Based on how they might impact on project results, risks should be recognized, sorted into categories, and given a priority order within this backlog [48]. This enables teams to set aside resources and time in subsequent sprints for tackling high-priority hazards.

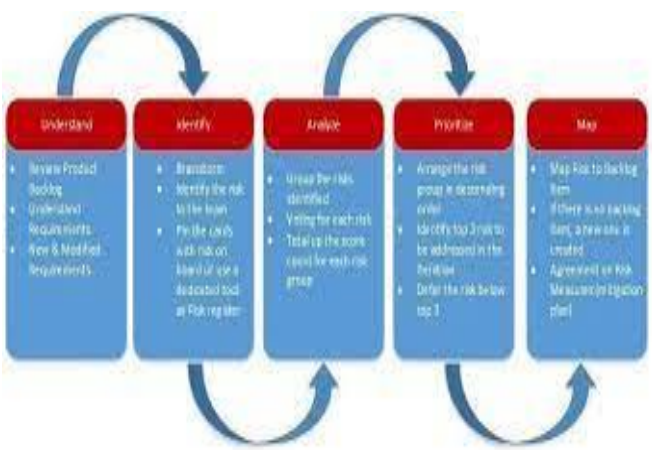

Fig. 4.3.1: Risk Management Processes

***Collaborative Risk Workshops*:**

Collective risk assessment, as well as mitigation planning, are facilitated by regular risk workshops comprising interconnected team members, such as data scientists, developers, as well as managers. The risk management method is strengthened by the honest discourse and knowledge exchange that these workshops promote.

***Automated Risk Tracking and Reporting*:**

By incorporating risk administration tools into Agile project oversight platforms, identified hazards, their status, and related mitigation measures are tracked automatically [49]. This gives stakeholders real-time visibility and guarantees that risks are continually tracked and dealt with.

Journal of Technology and Systems
ISSN : 2788-6344 (Online)
Vol. 6, Issue No. 3, pp 1 – 18, 2024
www.carijournals.org

***Risk-Informed Backlog Refinement*:**

New hazards could materialize, or preexisting dangers could change as the project moves forward. Teams' ought to examine and amend assessments of risk during backlog reduction sessions, revising priorities as well as mitigation plans as necessary [50]. By doing this, risk control is kept in line with the development of the project.

4.4 Dynamic Resource Allocation for Agile AI/ML Projects

To successfully manage computational assets in Agile AI/ML assignments, dynamic distribution of resources is a crucial component. Within Agile processes, this technological theme focuses on creating techniques for dynamic resource allocation based on shifting model intricacies and data quantities.

***Resource Scalability and Elasticity*:**

As models develop and data amounts change, Agile AI/ML projects may experience considerable fluctuations in resource requirements [51]. The continuous scaling either upward or downward of processing horsepower in reaction to these variations is made possible by dynamic allocation. This guarantees that the endeavor can change with the needs without sacrificing performance.

***Cost Optimization*:**

It is important to strike the correct balance between computing capacity and project expenses while optimizing the use of resources. Utilizing pay-as-you-go cloud services and auto-scaling strategies can help keep costs under control while guaranteeing that the required resources are accessible when needed.

***Adaptive Infrastructure*:**

Infrastructure that is adaptable is essential for Agile projects because needs frequently change. In order to guarantee that funds are readily accessible for tasks like training of models, testing, as well as deployment, the system should be built to handle various workloads effectively [52].

Fig. 4.4.1: Agile AI/ML Projects

Real-time Monitoring and Allocation:

It's crucial to continuously monitor how resources are being used. Implementing tools and approaches that offer immediate data on resource utilization will enable necessary allocation modifications to be made right away.

***Model Complexity Considerations*:**

The distribution of equipment should be changed in accordance with how sophisticated or specific a model is, or whether it needs a certain type of hardware (such as GPUs enabling deep learning) [53]. This makes sure that inductive and training tasks have access to the requisite computational resources.

EVALUATION AND CONCLUSION

5.1: Critical Evaluation

The research on "Risk Management in Agile AI/ML Projects: Assessing and Addressing Data as well as Model Risks" offers a thorough and relevant analysis of the complicated difficulties associated with incorporating AI/ML methods inside Agile frameworks. By concentrating on the specific hazards connected to information retention and model performance in Agile AI/ML initiatives, it fills a significant vacuum in the literature. The inductive research methodology, which is based on interpretivism, provides a solid framework for methodically investigating the topics at hand. Data effectiveness, model reliability, risk insertion, and the distribution of resources are among the four technological themes that offer a structured structure for addressing the complexities of Agile AI/ML initiatives. The viability in this study will depend on how well the suggested frameworks and tactics can be used in real-world situations. The effectiveness and viability of the suggested risk management techniques must be confirmed through rigorous evaluation and validation in actual Agile AI/ML projects. Furthermore, it is essential to keep the research current in an area that is continually evolving. The relevance and effect of the findings must be maintained by regular updates as well as adaptability to new AI/ML and Agile approaches.

5.2 Research recommendation

To ensure the efficacy and applicability of risk management frameworks in Agile AI/ML projects, it is essential to conduct empirical research that provides tangible evidence of their effectiveness. Continuous engagement with stakeholders including project managers, technicians, and data scientists is critical to ensure that risk identification and mitigation strategies remain aligned with evolving project needs. Furthermore, the adoption of advanced tools and technologies that facilitate model robustness, explicability, and dynamic resource allocation is crucial to maintaining the cutting-edge in AI/ML project management. Ethical and regulatory compliance must also be rigorously maintained, particularly in sensitive areas, to ensure the security and privacy of data. Additionally, conducting longitudinal studies can provide insights into the long-term effectiveness and adaptability of risk management strategies, highlighting their practical implications in real-world settings.

5.3 Future work

Automated Risk Identification: Create advanced tools and algorithms to automatically identify and evaluate risks in Agile AI/ML applications. The procedure for handling risks would be streamlined, and effectiveness would rise.

Dynamic Risk Response Strategies*:* Look into dynamic reaction tactics that can instantly adjust to changing hazards. This would necessitate the creation of intelligent systems that could modify mitigation measures in response to shifting project circumstances.

Ethical AI Guidelines: Establish thorough ethical standards that are applicable just to Agile Artificial Intelligence and projects, covering topics like fairness, openness, and responsibility [55]. This guarantees that AI systems created in agile environments comply with moral principles.

AI Governance Frameworks: Making use of project management approaches, develop governance frameworks specifically for Agile AI/ML initiatives. This would offer a methodical way to handle risks in Agile operations.

Meta-Analysis of Agile AI/ML Projects: Agile AI/ML Meta-analyses Projects To find underlying trends, prevalent risk patterns, as well as best practices across multiple domains and sectors, conduct a comprehensive review of Agile AI/ML initiatives.

5.4 Conclusion:

This study effectively develops a systematic approach to managing data and model risks in Agile AI/ML projects, providing a crucial enhancement to current methodologies. By focusing on the integration of risk management within Agile frameworks, it ensures that risk assessment and mitigation are central throughout the project lifecycle. The recommendations for empirical validation and continued adaptation of risk management strategies ensure that the framework remains relevant and effective in dynamic project environments. This research not only contributes to theoretical understanding but also offers practical guidance, fostering more reliable and efficient project outcomes in the rapidly evolving fields of AI and ML.

REFERENCES

[1] Boukherouaa, E.B., Shabsigh, M.G., AlAjmi, K., Deodoro, J., Farias, A., Iskender, E.S., Mirestean, M.A.T. and Ravikumar, R., 2021. *Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance*. International Monetary Fund.

[2] AlAjmi, K., Deodoro, J., Farias, A., Iskender, E.S., Mirestean, A.T. and Ravikumar, R., Powering the Digital Economy.

[3] Mattsson, U., 2023. *Controlling Privacy and the Use of Data Assets-Volume 2: What is the New World Currency–Data or Trust?*. CRC Press.

[4] Lennerz, J.K., Salgado, R., Kim, G.E., Sirintrapun, S.J., Thierauf, J.C., Singh, A., Indave, I., Bard, A., Weissinger, S.E., Heher, Y.K. and de Baca, M.E., 2023. Diagnostic quality model (DQM): an integrated framework for the assessment of diagnostic quality when using AI/ML. *Clinical Chemistry and Laboratory Medicine (CCLM)*, *61*(4), pp.544-557.

[5] Verleyen, W. and McGinnis, W., 2022. Framework for disruptive AI/ML Innovation. *arXiv preprint arXiv:2204.12641*.

[6] Ashraf, I., Zikria, Y.B., Garg, S., Park, Y., Kaddoum, G. and Singh, S., 2022. Zero touch networks to realize virtualization: Opportunities, challenges, and future prospects. *IEEE Network*, *36*(6), pp.251-259.

[7] McGinnis, W., 2022. Framework for disruptive AI/ML Innovation. *arXiv preprint arXiv:2204.12641*.

[8] Novak, W. and CARNEGIE-MELLON UNIV PITTSBURGH PA, 2021. Artificial Intelligence (AI) and Machine Learning (ML) Acquisition and Policy Implications.

[9] Trujillo, S., Sabuj, S.R. and Bartels, R., 2023. University Medical Center Utrecht, Utrecht University, Utrecht, Netherlands, 5 Department of Medical Microbiology, University Medical Center Utrecht, Utrecht University, Utrecht, Netherlands. *Surfacing best practices for AI software development and integration in healthcare*, p.14.

[10] Elbegzaya, T., 2020. Application AI in Traditional Supply Chain Management Decision-Making.

[11] Millar, G., Kafchitsas, A., CLS, O.M., Kourtis, A., Xilouris, G., Christopoulou, M., Kolometsos, S., de Oca, E.M., MI, H.N.N., Pastor, A. and Fernandez, S., 2019. INtelligent security and pervasive trust for 5G and beyond. *Eur. Commission, Germany, Tech. Rep. H2020-EU*, *2*(1).

[12] Krishankumar, R. and Ecer, F., 2023. Selection of IoT service provider for sustainable transport using q-rung orthopair fuzzy CRADIS and unknown weights. *Applied Soft Computing*, *132*, p.109870.

[13] Luo, M., 2022, December. Future Lies with Edge Computing. In *International Conference on Edge Computing* (pp. 80-106). Cham: Springer Nature Switzerland.

[14] Ashok, B. and Srivastava, S., 2021. LEADING THROUGH DISRUPTIONS A DISTRIBUTED LEADERSHIP MODEL FOR BANKS IN INDIA. *India Banking and Finance Report 2021*, p.3.

[15] Carlsen, A., 2020. *A self-assessment model for intelligent predictive maintenance analytics: An update of the Analyses Module in the Maintenance Baseline Study* (Master's thesis, University of Stavanger, Norway).

[16] Andresky, N. and Taliaferro, A., 2019. Operationalizing artificial intelligence for multi-domain operations. *Tech. Rep.*

[17] Huang, Y. and Chen, Y., 2020. Autonomous driving with deep learning: A survey of state-of-art technologies. *arXiv preprint arXiv:2006.06091*.

[18] Jägare, U., 2019. *Data science strategy for dummies*. John Wiley & Sons.

[19] Ahrens, J., Boehnlein, A., Carlson, R., Elliot, J., Fagnan, K., Ferrier, N., Foster, I., Gimpel, L., Shalf, J. and Ratner, D., 2022. *Envisioning Science in 2050*. USDOE Office of Science (SC)(United States).

[20] Zaichkowsky, T.M., 2020. *Systems architecture perspective on digital transformation for financial services* (Doctoral dissertation, Massachusetts Institute of Technology).

[21] Hamidi, A., 2021. *Machine Learning Engineering: An Exploratory Study of Challenges and Practices* (Doctoral dissertation, Ecole Polytechnique, Montreal (Canada)).

[22] McGrath, M.J., Kennedy, J., Jensen, J., Crompton, S., Queralt, A., Dizdarevic, J., Stanovnik, S., Černivec, A., Bizjak, M., Modic, J. and Font, R.S., D2. 3 Tracking Scientific, Technology and Business Trends (Version 3).

[23] Mazhar, N., Salleh, R., Hossain, M.A. and Zeeshan, M., 2020. SDN based intrusion detection and prevention systems using manufacturer usage description: A survey. *International Journal of Advanced Computer Science and Applications*, *11*(12).

[24] Da Silva, M., Flood, C.M. and Herder, M., 2022. Regulation of health-related artificial intelligence in medical devices: the Canadian story. *UBCL Rev.*, *55*, p.635.

[25] Hurtado Requena, S.J., 2023. Integration and analysis of biomedical data from multiple clinical trials.

[26] Stanton, B., Cirincione, G., Pham, T., Fischer, G., Ross, S., Whipps, G., Wiegmann, D. and Bennett, K., 2020. US Army Artificial Intelligence Innovation Institute (A2I2) Aiding Multi-Domain Operations (MDO). *CCDC Army Research Laboratory Adelphi United States*.

[27] Kesharwani, S., 2019. Proclamation from Editor's Inscription Counter. *CYBERNOMICS*, *1*(7), pp.1-4.

[28] Rainie, L., Anderson, J. and Vogels, E.A., 2021. Experts doubt ethical AI design will be broadly adopted as the norm within the next decade. *Pew Research Center*, *16*.

[29] Pierre, A., 2022. *Leadership of Human-Machine Teams in Military Environments: An Exploratory Framework* (Doctoral dissertation, Regent University).

[30] Cavalcante, I.M., Frazzon, E.M., Forcellini, F.A. and Ivanov, D., 2019. A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *International Journal of Information Management*, *49*, pp.86-97.

[31] Sharma, K., Qian, F., Jiang, H., Ruchansky, N., Zhang, M. and Liu, Y., 2019. Combating fake news: A survey on identification and mitigation techniques. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *10*(3), pp.1-42.

[32] Ivanov, D., Dolgui, A., Das, A. and Sokolov, B., 2019. Digital supply chain twins: Managing the ripple effect, resilience, and disruption risks by data-driven optimization, simulation, and visibility. *Handbook of ripple effects in the supply chain*, pp.309-332.

[33] Castro, D.C., Walker, I. and Glocker, B., 2020. Causality matters in medical imaging. *Nature Communications*, *11*(1), p.3673.

[34] Obrenovic, B., Du, J., Godinic, D., Tsoy, D., Khan, M.A.S. and Jakhongirov, I., 2020. Sustaining enterprise operations and productivity during the COVID-19 pandemic:"Enterprise Effectiveness and Sustainability Model". *Sustainability*, *12*(15), p.5981.

[35] Sharma, R., Shishodia, A., Kamble, S., Gunasekaran, A. and Belhadi, A., 2020. Agriculture supply chain risks and COVID-19: mitigation strategies and implications for the practitioners. *International Journal of Logistics Research and Applications*, pp.1-27.

[36] Hotle, S., Murray-Tuite, P. and Singh, K., 2020. Influenza risk perception and travel-related health protection behavior in the US: Insights for the aftermath of the COVID-19 outbreak. *Transportation Research Interdisciplinary Perspectives*, *5*, p.100127.

[37] Thiebes, S., Lins, S. and Sunyaev, A., 2021. Trustworthy artificial intelligence. *Electronic Markets*, *31*, pp.447-464.

[38] Realmonte, G., Drouet, L., Gambhir, A., Glynn, J., Hawkes, A., Köberle, A.C. and Tavoni, M., 2019. An inter-model assessment of the role of direct air capture in deep mitigation pathways. *Nature communications*, *10*(1), p.3277.

[39] Bommasani, R., Hudson, D.A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M.S., Bohg, J., Bosselut, A., Brunskill, E. and Brynjolfsson, E., 2021. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*.

[40] Amanullah, M.A., Habeeb, R.A.A., Nasaruddin, F.H., Gani, A., Ahmed, E., Nainar, A.S.M., Akim, N.M. and Imran, M., 2020. Deep learning and big data technologies for IoT security. *Computer Communications*, *151*, pp.495-517.

[41] Tang, B., Wang, X., Li, Q., Bragazzi, N.L., Tang, S., Xiao, Y. and Wu, J., 2020. Estimation of the transmission risk of the 2019-nCoV and its implication for public health interventions. *Journal of clinical medicine*, *9*(2), p.462.

[42] World Health Organization, 2021. Strategic toolkit for assessing risks: a comprehensive toolkit for all-hazards health emergency risk assessment.

[43] Gerry, S., Bonnici, T., Birks, J., Kirtley, S., Virdee, P.S., Watkinson, P.J. and Collins, G.S., 2020. Early warning scores for detecting deterioration in adult hospital patients: systematic review and critical appraisal of methodology. *bmj*, *369*.

[44] Sarker, I.H., Kayes, A.S.M., Badsha, S., Alqahtani, H., Watters, P. and Ng, A., 2020. Cybersecurity data science: an overview from machine learning perspective. *Journal of Big data*, *7*, pp.1-29.

[45] Ngo, P.T.T., Panahi, M., Khosravi, K., Ghorbanzadeh, O., Kariminejad, N., Cerda, A. and Lee, S., 2021. Evaluation of deep learning algorithms for national scale landslide susceptibility mapping of Iran. *Geoscience Frontiers*, *12*(2), pp.505-519.

[46] Burgos, D. and Ivanov, D., 2021. Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review*, *152*, p.102412.

[47] Anderegg, W.R., Trugman, A.T., Badgley, G., Anderson, C.M., Bartuska, A., Ciais, P., Cullenward, D., Field, C.B., Freeman, J., Goetz, S.J. and Hicke, J.A., 2020. Climate-driven risks to the climate mitigation potential of forests. *Science*, *368*(6497), p.eaaz7005.

[48] Carlini, N., Tramer, F., Wallace, E., Jagielski, M., Herbert-Voss, A., Lee, K., Roberts, A., Brown, T., Song, D., Erlingsson, U. and Oprea, A., 2021. Extracting training data from large language models. In *30th USENIX Security Symposium (USENIX Security 21)* (pp. 2633-2650).

[49] Rathore, S., Kwon, B.W. and Park, J.H., 2019. BlockSecIoTNet: Blockchain-based decentralized security architecture for IoT network. *Journal of Network and Computer Applications*, *143*, pp.167-177.

[50] Alegbeleye, O.O. and Sant'Ana, A.S., 2020. Manure-borne pathogens as an important source of water contamination: An update on the dynamics of pathogen survival/transport as well as practical risk mitigation strategies. *International journal of hygiene and environmental health*, *227*, p.113524.

[51] Sellgren, C.M., Gracias, J., Watmuff, B., Biag, J.D., Thanos, J.M., Whittredge, P.B., Fu, T., Worringer, K., Brown, H.E., Wang, J. and Kaykas, A., 2019. Increased synapse elimination by microglia in schizophrenia patient-derived models of synaptic pruning. *Nature neuroscience*, *22*(3), pp.374-385.

[52] Scher, J.U., Ogdie, A., Merola, J.F. and Ritchlin, C., 2019. Preventing psoriatic arthritis: focusing on patients with psoriasis at increased risk of transition. *Nature Reviews Rheumatology*, *15*(3), pp.153-166.

[53] HaddadPajouh, H., Dehghantanha, A., Parizi, R.M., Aledhari, M. and Karimipour, H., 2021. A survey on internet of things security: Requirements, challenges, and solutions. *Internet of Things*, *14*, p.100129.

[54] Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M.D., Barker, K. and Al Khaled, A., 2019. Resilient supplier selection and optimal order allocation under disruption risks. *International Journal of Production Economics*, *213*, pp.124-137.

[55] Shuja, J., Alanazi, E., Alasmary, W. and Alashaikh, A., 2021. COVID-19 open source data sets: a comprehensive survey. *Applied Intelligence*, *51*, pp.1296-1325.