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Original Article

Intelligent Risk Assessment and Classification in Project Management Using Data-Driven AI Models

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Abstract: *The rapid evolution of globalization, digitalization, and technological innovations has led to an increase in complexity of the project management domain; therefore, assessing and classifying the risks involved becomes increasingly complicated. The conventional techniques of risk management, which include risk identification, analysis, and forecasting, cannot adequately detect and control complex risks related to finance, operations, technology, strategy, and cybersecurity. In view of the aforementioned difficulties, the use of "Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), predictive analytics, and big data" has been identified as a smart way to improve the management of the project risks. This study is intended to review the contribution of AI-based solutions for risk assessment and classification in project management settings. This study discusses several types of AI algorithms and predictive models, including "Decision Tree, Random Forest, Support Vector Machine, Artificial Neural Networks, Recurrent Neural Network, and Long Short-Term Memory Models", focusing on their uses, strengths, and weaknesses in project risk management. AI enhances the accuracy of predictions and decisions, enabling real-time monitoring and planning by uncovering patterns of risks and developing measures to mitigate them. Yet, several barriers remain that prevent the implementation of intelligent risk management practices, including data integrity problems, cybersecurity concerns, ethical issues, AI bias, lack of transparency, and absence of real-life validation studies. This paper concludes that the implementation of Explainable AI (XAI), real-time analysis capabilities, cloud computing technologies, and digital twins can improve the performance of intelligent risk management systems.*

Keywords: *Artificial Intelligence, Project Management, Risk Classification, Machine Learning, Deep Learning, Predictive Analytics, Data-Driven AI Models, Natural Language Processing, Fuzzy Logic, Hybrid AI Systems.*

1. Introduction

Project management practices have evolved in conjunction with the growth of industry, technological progress, and organization. In early industrial development, project management depended on manual planning, human judgment, and conventional control systems to manage processes and uncertainties and plays an important role in achieving organizational goals by ensuring the successful execution of projects within defined constraints of time, cost, quality, and scope [1]. However, modern projects are exposed to multiple uncertainties including financial instability, operational disruptions, technical failures, cybersecurity threats, stakeholder conflicts, and environmental changes. These uncertainties create risks that can negatively influence project outcomes if not effectively identified and managed. Methods such as "Gantt charts, Critical Path Method (CPM), Program Evaluation and Review Technique (PERT)", and qualitative methods of assessing risks have been extensively used to ensure that projects are performed efficiently and that any risks can be identified. Even though the above strategies played an important role in making projects well organized, they lack the intelligence needed in today's environment [2].

In light of the rapid growth in globalization, digitization, and technology adoption, today's projects have become increasingly complex in nature, involving a great degree of interconnection and generation of vast volumes of data. Today's companies may face various types of project-related risks, such as financial risks, disruptions in business activities, threats connected to cybersecurity, lack of sufficient resources, technical faults, regulatory concerns, and others. The increasing complexity associated with modern projects makes traditional project risk assessment methods incapable of accurately predicting, classifying, and mitigating problems that emerge throughout the process of their implementation. As a consequence, companies begin to turn to advanced data-based decision support systems instead of relying on traditional project risk management techniques. Developments in terms of "AI, ML, big data analytics, and predictive modeling" have led to a number of modifications within the sphere of project management and made it possible to use novel approaches to risk evaluation and classification. Thanks to AI, it becomes possible to examine great amounts of data regarding a particular project and classify the risks and uncertainties that might emerge. The rise of AI, ML, "Big Data Analytics" (BDA), DL, and Predictive Modeling brings with it intelligent risk assessment and categorization, bringing about revolutionary change in the field of project management [3]. AI systems are able to mine through enormous data that is either structured or unstructured to

identify patterns, make predictions, and classify risk elements accurately. Contrary to traditional approaches of risk assessment and management, where decisions and assumptions are often made without considering historical data, data-driven AI models are able to facilitate the identification of risk patterns and prediction of future occurrences. Through data-driven AI models, it becomes possible for project managers to automatically learn from previous projects through the identification of risk patterns, making accurate predictions, and the categorization of risks according to their respective impact levels. ML, neural networks, fuzzy logic, and predictive analytics are some of the advanced AI techniques that can help enhance the accurateness and competence of risk analysis procedures [4].

1.1. Research Aim and Objectives

- To investigate the contribution of AI in risk identification and categorization of the project.
- To study the application of AI in project risk management.
- To determine the efficiency of AI-based predictive models in project management.
- To understand the obstacles faced by AI in project management.
- To determine future scopes for sustainability of AI in project management.

1.2. Research Question

RQ1: How effective are explainable AI models in project risk classification across industries?
RQ2: What differences exist in AI-driven risk assessment between construction, IT, and healthcare projects?
RQ3: How does model explainability influence stakeholder trust in project risk decision-making?

1.3. Structure of Paper

It is methodically organized into four main parts to enable an overall comprehension of intelligence risk assessment through AI technology in project management. Firstly, the background part outlines the evolution of project management, increased complexity in projects, and the beginning of AI, ML and other predictive tools. Secondly, the methodology of the research is described, which includes research design, sources of data, and literature choice criterion. Thirdly, the literature review describes the topics covered, including risk management, use of AI technology, data-driven decision making, and comparative study of different AI algorithms. Finally, conclusions of the research are made based on the above findings.

2. Research Methodology

2.1. Research Design

The investigation employs a qualitative and systematic review research methodology to examine the role of data-driven AI models in intelligent risk assessment and classification within project management. The research focuses on critically analyzing existing literature related to AI-driven project risk management systems. Both traditional and modern risk management approaches are reviewed to understand the transition from conventional risk assessment methods to intelligent AI-based predictive systems.

2.2. Data Collection Sources

The data for the study have been collected from credible academic databases and scholarly sources, including “Google Scholar, Scopus, ScienceDirect, SpringerLink, IEEE Xplore, and peer-reviewed journals”. The selected literature mainly focuses on “AI, ML, DL, NLP, predictive analytics, big data analytics, and project risk management”. The timeframe of the study ranges from 2020 to 2026.

2.3. Inclusion and Exclusion Criteria

The study includes “peer-reviewed journal articles, conference papers, and case studies” directly linked to AI implementation in project risk assessment and management. Studies unrelated to the topic, duplicated publications, and irrelevant sources were excluded from the analysis to maintain research quality and relevance.

2.4. Data Analysis Method

The collected literature was examined using thematic and comparative analysis methods. The study identifies major AI algorithms, their applications, advantages, disadvantages, implementation challenges, and future opportunities in intelligent project risk management. Comparative analysis of predictive AI models was also conducted to evaluate their effectiveness in project risk assessment and forecasting.

3. Literature Review

3.1. Evolution of AI in Project Risk Management

3.1.1. Concept of Risk Management in Project Management

Project management in case of risk management refers to the process whereby risks are identified, assessed, analyzed, controlled, and minimized where possible. There is always uncertainty involved in any project regardless of its size and nature [5]. In this regard, risk management has become a key part of the managerial process that will reduce the negative impact and improve the overall success of the project implementation. Traditional risk management of projects had more emphasis on handling the issues when they arise. Risk management suggests that project uncertainties are inevitable. For example, financing, technology, lack of resources, problems with logistics, changes in legislation and regulation, environmental conditions, cyber threats, market instability, and human errors are some of the risks that might occur in projects. For improving project effectiveness, innovation, and competitiveness, risk management should also address the presence of positive uncertainties and opportunities. Management relies on risk management to improve planning, resource allocation, scheduling, financial control, and organizational resilience [6]. By assessing potential risks during planning, organizations can prepare contingency plans, allocate resources, and improve communication to overcome project implementation risks. Consequently, there would be high-quality decisions made and the ability of organizations to cope with uncertainties would improve. Moreover, creation of mechanisms to assess the performance of projects would foster transparency in the process. A discussion of the critical appraisal of risk management in projects brings out the

strengths and weaknesses associated with the strategic use of risk management. Different methods that could be used in the identification of risks in projects include SWOT analysis, probability impact matrix, human judgment, Monte Carlo simulation, and FMEA [7].

3.2. Emergence of Artificial Intelligence in Management

Therefore, the use of AI in managing risks in the process of the project implementation should be regarded as a sort of evolutionary step in modern management decisions. Indeed, historically speaking, the project risk management has always relied on human intelligence, forecasting, and various statistical approaches to estimation, but at the same time these traditional approaches lack the necessary level of flexibility to meet modern challenges. New developments in digital transformation, computing technologies, cloud technologies, and data analytics have made it possible to incorporate intelligent technologies into project management systems [8]. In particular, technologies like ML, DL, and NLP helped to make improvements in existing project risk assessment techniques in terms of their ability to detect patterns and anomalies, predict results, monitor projects and make decisions [9]. Contemporary intelligent technologies have made it possible to use huge quantities of both organized and unorganized data to identify uncertainties and minimize risks in projects. Nevertheless, there are several issues associated with intelligent systems that should be addressed before implementing them in practice [10].

3.3. Data-Driven Decision Making

Decisions may now be based on project knowledge, not gut feelings, thanks to data-driven decision-making, which is why it is so important for risk management. A large volume of data is produced within project environments as a consequence of the use of various data-producing techniques like scheduling, financial data, procurement, resource allocation, stakeholder information, and performance data [11]. The combination of the data-driven approach with intelligent analysis makes it possible for companies to identify risk patterns that were not visible before, evaluate uncertainties, forecast future events, and objectively measure the results of projects. The traditional approach to decision-making was characterized by the use of insufficient data, presence of cognitive biases, and inability to identify risks. The emergence of such advanced technologies as BDA, ML, “Cloud Computing” (CC), and business intelligence solutions has made it possible to process project data and make timely predictions about project risks, automatically detect anomalies, and make evidence-based recommendations [12]. The other significant omission relates to the inadequate attention paid to Explainable Artificial Intelligence (XAI) in project risk management. Indeed, there are many AI and machine learning algorithms that operate in a "black-box" fashion, implying that it is rather hard to comprehend how the algorithm arrives at its decisions for the project manager or any other relevant stakeholders. In addition, very few researchers have explored the effect of model explainability on decision-making confidence and organizational adoption of AI systems.

Table I summarizes the comparative analysis of ML and DL algorithms, highlighting the strengths and limitations in this study

Table 1: Data-Driven AI Algorithm for Risk Assessment

Algorithm	Short Explanation	Major Applications in Project Management	Limitation / Problem Leading to Next Model
Decision Trees	A tree-structured algorithm that splits data into branches based on decision rules to classify risks and predict outcomes.	Risk severity prediction, project classification, cost estimation	Decision trees may become unstable and overfit complex project datasets, reducing prediction accuracy [13].
Random Forest	A type of ensemble learning that enhances prediction accuracy by reducing the effect of overfitting through the use of many decision trees.	Schedule delay prediction, financial risk analysis, resource planning	Random Forest improves accuracy but requires high computational resources and lacks interpretability [14].
Support Vector Machine (SVM)	A method for categorization that uses hyperplanes, or optimum decision boundaries, to divide risks into distinct groups.	Risk categorization, fraud detection, project success prediction	SVM performs poorly with very large datasets and complex nonlinear project relationships [15].
Logistic Regression	A statistical classification model that predicts the probability of project risks occurring.	Cost overrun prediction, project success probability analysis	Logistic regression assumes linear relationships and cannot effectively capture highly complex project patterns [16].
Naïve Bayes	A method that uses probability calculations to anticipate outcomes; it is based on Bayes' theorem.	Risk classification, issue prediction, document categorization	Naïve Bayes assumes feature independence, which is unrealistic in interconnected project risks [17].
K-Means Clustering	A clustering algorithm that groups similar project risks or stakeholders into clusters without labeled data.	Risk pattern discovery, stakeholder segmentation	K-Means struggles with irregular data shapes and sensitivity to cluster selection [18].

Hierarchical Clustering	A clustering method that creates hierarchical relationships among project risk groups.	Behavioral risk grouping, dependency analysis	Hierarchical clustering becomes computationally expensive for large project datasets [19].
Association Rule Mining	An algorithm used to discover hidden relationships and frequent patterns among project variables.	Dependency identification, risk relationship analysis	Association rules may generate too many irrelevant patterns and weak correlations[20].
Artificial Neural Networks (ANN)	AI models inspired by the human brain that learn nonlinear relationships between project variables.	Project failure prediction, financial risk scoring	ANN models require large datasets and often function as "black-box" systems with low explainability [21].
Recurrent Neural Networks (RNN)	Neural networks designed to process sequential and time-series project data.	Schedule forecasting, operational trend analysis	RNN models suffer from short-term memory limitations and vanishing gradient problems [22].
Long Short-Term Memory (LSTM)	For precise forecasting, state-of-the-art RNN models can remember long-term sequential data.	Dynamic risk monitoring, predictive maintenance, delay forecasting	LSTM models are computationally expensive and require extensive training time [23].

In a dynamic project environment, the graphic below shows the numerous hazards and their interconnections in a project management scenario. The graphic depicts several types of risks, including those pertaining to operations, finances, strategy, technology, and the outside world. Execution and performance of the project might be impacted by all of these risks [24]. The operational risks include inefficiency in operations, delays in schedules, insufficient resources, and disruptions in workflow. Financial risks encompass budget overruns, fluctuation in cash flow, inflationary trend, and limitations in financing. Strategic risks occur due to organizational misalignment, market fluctuation, policy change, and competition affecting the strategic objective of the projects. Technical risks consist of technical faults, including power failure, software problems, breaches in security, and any other technical issue that could affect the project process [25].

In smart project risk management, applications powered by AI use predictive analysis, monitoring, anomaly detection, and pattern recognition to analyze the above-discussed risk types. As opposed to traditional methods of risk assessment that classify each risk separately, data-based AI models make it possible to classify various connected risks simultaneously, making prediction more convenient and taking proactive actions. The interconnection diagram shown in Fig. 1 shows why it is essential to use AI-powered applications for analyzing interdependencies between risks.

Fig 1: Types of Project Risks

3.4. Advantages of Data-Driven AI Models for Project Risk Management

The AI models built rely on data have many benefits when employed to "project risk management", since through the use of intelligent systems, it is possible to conduct intelligent analysis of huge amounts of past and current data from various projects, discover hidden patterns, predict uncertainties, and make informed decisions. ML algorithms used by these systems continuously learn from all the past projects and enhance their predictive abilities to help project managers predict future problems such as schedule slippage, cost overruns, shortage of resources, failure of machines, and operational challenges [6]. Unlike the conventional methods of risk management that involve periodic evaluation of risks and analysis of past reports to predict potential risks, intelligent systems make it possible to monitor all the ongoing activities in projects including financial transactions, performance indicators, etc., in real time.

The next key benefit provided by the use of AI for assessing risks is the improvement in efficiency and strategic planning through effective decision-making. With the help of intelligent decision-making systems and analytics dashboards, project managers will be able to consider various scenarios of risk occurrence and mitigate them accordingly while distributing resources efficiently [26]. The absence of human bias in traditional risk assessment methods is another advantage of analytical models. This is because AI-driven systems create predictions using facts, rather than human opinion. Furthermore, unlike conventional risk assessment methods, AI-based models may examine several interconnected risk variables. By detecting wasteful processes, sustaining them, and assigning them appropriately, AI offers a chance to optimize resources and minimize expenses. To save money, AI may, for instance, foresee when machinery would break down, allowing for maintenance to be postponed [27]. Still, the effectiveness of the above-described benefits greatly depends on data and technology, which should be available and of high quality. Risk assessment using artificial intelligence is different for various industries including the construction sector, IT, and healthcare because

of the difference in the level of risks associated, as well as in operational environments. In construction-related projects, risk assessment is mostly done to identify possible dangers relating to safety risks, cost overrun, schedule delay, and resources management. In the IT field, risk assessment through artificial intelligence is used for detecting cyber risks, failure prediction, and performance management. Finally, healthcare projects risk assessment through artificial intelligence is mainly done for patient safety, compliance risks, and data security.

3.5. Related Work

Dorothea S. Adamantiadou's (2025) literature review examines project management with AI approaches. Cost estimating, duration projection, and risk assessment are crucial to project success. PRISMA was used to rigorously and transparently aggregate 97 peer-reviewed studies spanning 2011 to 2024. AI approaches like ML, DL, and hybrid models can improve PM processes throughout project planning, execution, and monitoring. To simplify understanding and implementation, decision trees depict AI approaches in PM phases and tasks. These include "hybrid AI models" that improve "risk assessment, duration forecasting, cost estimate, and project phase classification" to maximize AI integration. Despite these advances, dynamic project settings, verifying AI models with real-world data, and researching project closure are still lacking [28].

Kristijan Vilibić (2026) explore the risk management on significant construction projects is very important, but at the same time, it is challenging because of financial risks, safety issues, environmental problems, scheduling issues, and regulation-related risks. Using risk management, one can achieve optimization through cost control, disruption reduction, and decision-making effectiveness. Identifying risks and managing them in an early stage will contribute to optimizing the project. Experts and probabilistic models have difficulties with interpreting huge sets of data and dependencies between risks. Therefore, this study aims to use AI tools for analyzing the project's documentation and providing the first list of threats. The objective of the study is risk identification efficiency, risk management bias reduction, and risk identification alignment with PM2. Initial results suggest that AI can expand the scope of recognized risks and facilitate a systematic approach to risk management [29].

Andreea Geamanu (2026) examines the increasing application of AI in project management, especially risk analysis, where conventional methods do not have predictive capabilities. In this study, they have developed a risk identification and interpretation tool based on AI, ML, and documentation integration for project management teams. It was trained using 27 input attributes to predict risk type, effect, likelihood, and reaction using a "multi-output Decision Tree" and "Random Forest model". The model was applied to 5,000 project examples created by deterministic rules. Because their data set was based on deterministic rules, both models performed nearly perfectly in terms of categorization; nevertheless, Random Forest performed somewhat better when it came to predicting numerical values. Their model framework is validated by these data, but they do not know how accurate the predictions are. Their models are housed on a web application that includes features such as a risk management planning form, automatic PDF report generating, result saving, and predicted output visualization. The survey results show that mobile apps, dashboard visualizations, alerts, and AI-driven mitigation techniques are highly sought-after by users [30].

Philip Ugochukwu Ojiegbu (2025) presents the "LLM-Augmented Risk and Documentation Integration (LARDI) Framework", an integrated use of Large Language Models within IT risk and governance processes. Operational functions, governance controls, and performance indicators associated with ethical and effective usage are established via a thorough review and analysis of the relevant academic literature. The combination of probabilistic risk exposure and contextual knowledge gained from unstructured data is used in creating a quantitative risk scoring model. Results demonstrate that LLMs are advanced intelligence tools that contribute to increased early risk recognition and correct documentation, making compliance preparation easier. Sustained usage depends on ethical, security, and transformation challenges [31]. Model explainability significantly influences stakeholder trust in project risk decision-making because transparent AI systems provide clear reasoning behind predictions and classifications. When stakeholders understand how AI identifies and evaluates risks, they are more likely to trust the system and adopt AI-based recommendations in project management processes. Explainable AI also improves accountability, reduces uncertainty, and supports ethical decision-making. In contrast, black-box AI systems create concerns regarding transparency, bias, and reliability, which may reduce organizational confidence and limit AI adoption in real-world project environments.

This study summarizes the research focus, AI technique, methodology, key findings and strengths in Table II.

Table 2: Comparative Analysis of Literature Review

Author & Year	Research Focus	AI Techniques / Models Used	Methodology	Key Findings	Strengths
Dorothea S. Adamantiadou (2025)	Analysis of AI methods used in project	ML, DL, Hybrid AI Models	Comprehensive analysis of 97 peer-reviewed articles	AI models improve project planning,	Comprehensive systematic review covering broad AI applications in project management; strong conceptual framework for AI

	management, such as time and expense prediction and risk analysis		published between 2011 and 2024 using the PRISMA standard	execution, monitoring, risk assessment, duration forecasting, and cost estimation. Decision-tree frameworks simplified AI integration across PM phases.	integration
Kristijan Vilibić (2026)	AI-based risk identification in large construction projects	GPT-5, Gemini 2.5, Sonnet 4.5	AI analysis of project documentation for "Trg Pravde" judicial infrastructure project in Croatia	AI improved phase-specific risk identification, reduced human bias, expanded recognized risks, and aligned risk management with PM2 standards	Practical implementation of AI in real construction project environments; integration of advanced generative AI models
Andreea Geamanu (2026)	Development of AI-driven project risk identification and interpretation tool	Decision Tree, Random Forest, ML Models	Multi-output ML model trained on 5000 project cases using 27 input variables with web application integration	Random Forest slightly outperformed Decision Tree in numeric prediction. AI tool enabled automated PDF reports, dashboards, notifications, and mitigation planning support	Strong predictive framework with integrated visualization and automation features; high user acceptance for AI-based mitigation systems
Philip Ugochukwu Ojiegbu (2025)	Integration of Large Language Models (LLMs) into IT risk management and governance systems	Large Language Models (LLMs), Quantitative Risk Scoring Models	Literature review and development of the LARDI Framework integrating contextual and probabilistic risk analysis	LLMs improved early risk recognition, documentation accuracy, and compliance readiness through contextual analysis of unstructured data	Innovative integration of LLMs with governance and documentation systems; strong focus on contextual intelligence

Research Gap: Despite its increasing popularity for risk assessment and categorization purposes, many research gaps have been identified within the topic of AI application in project risk management. The major emphasis has been made on the accuracy of AI prediction techniques, as well as development and analysis of theoretical AI models. Meanwhile, few works have addressed the application of AI approaches to actual risk management processes within projects, despite its obvious importance for practical decision-making. Furthermore, comparative evaluation of AI models in

terms of their performance in construction, information technology, and healthcare industries is lacking in the existing literature. The other significant omission relates to the inadequate attention paid to Explainable Artificial Intelligence (XAI) in project risk management. Indeed, there are many AI and machine learning algorithms that operate in a "black-box" fashion, implying that it is rather hard to comprehend how the algorithm arrives at its decisions for the project manager or any other relevant stakeholders. In addition, very few researchers have explored the effect of model explainability on decision-making confidence and organizational adoption of AI systems.

3.6. Challenges Impacting Project Management Data-Based AI Models

Limited Real-World Validation issue faced by AI-based projects involving management is the lack of testing due to the fact that most intelligent systems have been tested on controlled, organized, or historical data. Market conditions, customer needs, possible disruptions, resource constraints, and other factors may impact the process of managing real-world projects [32]. This means that even a perfectly designed algorithm might not work effectively at predicting outcomes in real-time project management. The problem can affect the process of assessing risks, estimating costs, making a schedule, and making decisions in the management process. Also, organizational structure, type of projects, and available data reduce the scope of application. The ethical concerns and biases of project management data-based AI models are linked to the usage of historical and organizational data as an AI training material. Ethical concerns will affect project management areas such as allocation of resources, employee performance assessments, budget development, recruiting practices, and risk categorization. AI bias unintentionally favors certain decisions, projects, teams, and management practices by ignoring other important factors involved in those decisions. Issues of transparency, accountability, data privacy, and AI responsibility come up as well. The majority of sophisticated models are black-box systems that make project managers struggle to understand the process of choice-making and risk assessments done by the AI. Lack of explanations might lead to loss of trust in the technology and inability to exercise managerial responsibility [33]. AI project management models use sensitive organizational and personal data which creates issues related to confidentiality, potential misuse of data, and cyberattacks. The lack of quality and availability of data is a significant barrier to AI models in project management because AI relies on reliable, complete, coherent, and available data about projects. Project-related data in many organizations may be inconsistent or stored in different databases, rendering it difficult for the AI system to analyze and assess. The data could be incomplete, outdated, duplicated, or incorrect, which could affect the accuracy of the model's predictions about risk, costs, and schedules. Data quality can impact the decision-making ability and predictions made using the project management data AI models. Due to the lack of historical and real-time data, there is limited flexibility in the ML models' ability to adapt to new conditions while executing projects. Risk assessment systems utilizing intelligence are complex and include data collection techniques, report generation methodologies, and data governance mechanisms. Companies implementing AI-driven project management tools may experience difficulties with project forecasting, automation, and strategy formulation. Privacy of data is yet another problem, considering that many of these AI models collect and assess information on the stakeholders, individuals working within the organizations, contracts, funds, and future strategies of the enterprises [34]. Any improper usage of this information can cause violations of the relevant laws and organizational practices. Also, the chances of data being misused or used unlawfully may increase due to weak encryption, lack of control measures, and failure to employ effective mechanisms for managing this data securely. In terms of the management of projects, cybersecurity may pose threats to the effectiveness of monitoring risks online, decrease the reliability of stakeholder trust, and affect the forecasting capacity of AI. In order to ensure the appropriate and safe application of AI in the process of project management, it is necessary for enterprises to develop efficient cybersecurity measures and data security laws. The new study results indicate the effectiveness of project management methods based on AI concerning the development of automation, predictive analysis, and risk assessment. Nevertheless, some disadvantages should be taken into account: the absence of practical validation, inadequate data reliability, cybersecurity problems, and ethical questions. The choice may be influenced by the subjective factor caused by the use of historical data, whereas the implementation of black box systems hampers responsibility and visibility. Moreover, there is a danger of violating privacy, poor data handling, and no standardized data exchange in projects.

4. Conclusion

The capability of organizations to recognize, foresee, and adapt to the uncertainties related to projects is significantly enhanced through the application of “AI, ML, DL, NLP, and hybrid systems analytics”. Some of the benefits of applying AI technology include predictive intelligence, real-time surveillance, automatic classification, and data-driven decision-making processes, compared to the conventional risk management practices that involve manual assessment and judgment techniques. The paper endeavors to bridge the significant gap in project risk management based on AI by investigating the application of explainable AI systems to project risk management in various industries. The primary problem addressed is the tendency by past research to focus more on accuracy and less on other important factors such as transparency, trust, and comparison between different industries such as construction, IT, and health care. It should be noted that AI models currently being used are largely black box models, and therefore have lower accountability levels. These innovations enable organizations from different sectors to improve their project planning, resource allocation, efficiency, cost management, and responsiveness. From this study, it becomes apparent that project management strategies powered by AI technology can control complex risk factors associated with projects, including “operational risk, financial risk, technological risk, strategic risk, and external risk”. One AI model can rely heavily on historical and corporate data,

which can be problematic in a dynamically changing environment related to project work. As far as further research regarding intelligent project risk assessment is concerned, more efforts need to be invested into developing flexible, transparent, and pragmatic solutions based on AI. The implementation of Explainable AI (XAI), allowing for creating transparent and understandable decision-making processes, will be critical for the future. Another promising avenue for future research includes combining real-time analytics, the Internet of Things, CC, and the digital twin technology with AI-based systems of project management. This combination will create opportunities for monitoring, forecasting, and mitigating risks dynamically as a result of changing project conditions. In addition to that, policy frameworks should guarantee that the organization monitors the AI-based decision-making process to promote human-focused use of AI. Rather than eliminating the human aspect of strategic decision-making, AI tools need to facilitate decision-making. Organizational readiness and resistance to technological changes could be addressed by training employees to become literate about technologies. Before applying any AI algorithms, organizations need to establish ethical review committees in order to evaluate whether there is any sort of bias and whether the technology is fair enough. Validation and performance testing in the real-world setting need to be standardized to ensure that models are stable and flexible under different project conditions.

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