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AUTOMATION OF CONSTRUCTION RISK MANAGEMENT PROCESSES BASED ON MACHINE LEARNING ALGORITHMS: PROBLEM FORMULATION AND EFFICIENCY ANALYSIS

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Abstract

The article examines theoretical and applied aspects of automating construction risk management processes using machine learning algorithms. It is shown that under conditions of high uncertainty in construction projects, traditional risk management approaches are limited in terms of responsiveness and forecasting accuracy. A conceptual model of risk management automation is considered, taking into account schedule, cost, quality, resource, and contractual factors. The main classes of machine learning algorithms applicable to risk prediction and ranking are analyzed. Based on a comparative analysis of published practical cases from large construction companies, the applied effects of implementing algorithmic solutions are demonstrated, including reduced losses, increased transparency of control, and improved quality of managerial decision-making.

Keywords: *construction risk management, machine learning, automation, construction projects, risk prediction, digitalization of construction, efficiency analysis*

Introduction

Amid the growing complexity of investment and construction projects, rising resource costs, and stricter requirements for deadlines and quality, risk management has become a fundamental condition for project sustainability. The construction industry is characterized by a high level of uncertainty driven by organizational, financial, technological, contractual, logistical, and external economic factors. At the same time, traditional risk management approaches remain largely reactive, as they rely on expert judgment, retrospective analysis, and fragmented information processing, which limits the timely detection of threats and weakens managerial responsiveness. Under conditions of digital transformation, the importance of tools capable of automated data analysis, identifying hidden interdependencies, and forecasting deviations at early stages is increasing.

One of the most promising ways to address this challenge is the use of machine learning (ML) algorithms, which improve the accuracy of risk identification, formalize probability assessment, and expand the analytical capabilities of project management systems. The aim of the study is to formulate the task of automating construction risk management based on ML and to assess its effectiveness in decision-support systems. The scientific novelty lies in substantiating construction risk management automation as an integrated analytical framework combining risk identification, classification, forecasting, and prioritization. The practical significance of the study is associated with improving the validity of managerial decisions and enabling earlier detection of critical deviations in time, cost, and quality.

Methods

The study employs a combination of general scientific and applied research methods, including the analysis and synthesis of academic literature on construction risk management, the digitalization of construction processes, and the use of ML algorithms for forecasting and decision support. The methodological foundation is based on systems and process-oriented approaches, which make it possible to examine risk management as a continuous cycle of identification, assessment, monitoring, and mitigation throughout the implementation of a construction project. To formalize the problem setting, structural and functional analysis, risk classification, and comparison of ML algorithms with typical construction risk management tasks were applied. The effectiveness of automation was examined through a comparative analysis of published studies and practical cases describing algorithm-based approaches in construction risk management, with attention to reported effects related to risk detection, schedule control, rework prevention, and decision-support quality.

Results

To achieve the objective of the study, the theoretical foundations of risk-oriented management in construction were examined, the potential for integrating ML algorithms into risk identification, assessment, and forecasting procedures was analyzed, and practical aspects of evaluating their effectiveness in the context of construction project implementation were presented.

Theoretical and methodological framing of construction risk management automation

In academic and applied discourse, construction risk can be defined as the probability of events and conditions that may cause deviations from project targets in terms of time, cost, quality, safety, and contractual performance (Teymoori S. et al., 2026). In construction, risks arise not within a single local process but at the intersection of design, procurement, construction operations, contractor coordination, regulatory procedures, and the external macroeconomic environment. Therefore, risk management should be viewed not as an occasional expert assessment but as a continuous process of identification, classification, monitoring, and preventive response. The relevance of this approach is reinforced by the scale of the sector itself: according to Deloitte, the global construction market may grow from \$11.39 trillion in 2024 to \$16.11 trillion by 2030, while smart construction has already moved from an experimental concept to an operational necessity (Deloitte, 2025).

Table 1. *Classification of construction risks for automated analysis (Dikmen I. et al., 2025; Hrebeniuk O., 2026)*

Risk category	Risk group	Typical manifestations	Data for automated analysis
Internal risks	Schedule risks	Delays in project stages. Deviations from the planned timeline. Cascading shifts of subsequent activities.	Project schedules. Actual progress data. Construction logs.
	Cost risks	Budget overruns. Increase in material and labor costs. Unplanned expenses.	Cost estimates. Payment records. Material price data. Labor indicators.

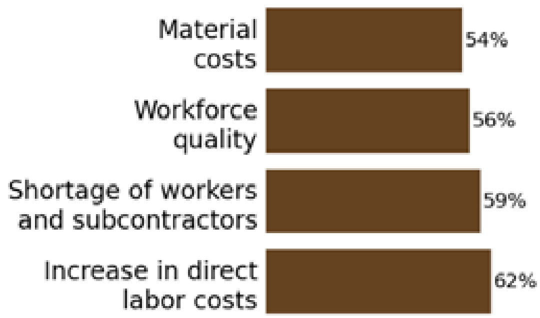
Risk category	Risk group	Typical manifestations	Data for automated analysis
	Resource risks	Shortage of workforce. Lack of equipment or materials. Limited subcontractor capacity.	Workforce data. Supply chain data. Equipment utilization metrics.
	Quality and production risks	Defects in construction works. Rework. Decrease in productivity.	Inspection reports. Quality control data. Production reports.
	Contractual and regulatory risks	Delays in approvals and permits. Payment delays. Contractual disputes.	Contract terms. Permit documentation. Payment discipline data.
External risks	External environment risks	Inflation. Supply chain disruptions. Regulatory changes. Macroeconomic instability.	Market indicators. Logistics data. Regulatory updates.

The multidimensional nature of construction projects requires a structured classification of risks by source and impact. Table 1 presents the main risk groups that form the uncertainty profile of construction projects.

The systemic nature of construction risks is confirmed by recent quantitative evidence. According to Autodesk, a typical construction project involves an average of 42 external stakeholders across its lifecycle, which increases the likelihood of information loss, coordination failures, and cascading errors between project stages. The same source reports that 89% of construction executives experienced payment delays during the previous year (Autodesk, 2025). Under such conditions, static risk registers and periodic reporting are insufficient; effective risk management requires an architecture capable of processing multiple interrelated factors in near real time and detecting early signs of deviation before critical consequences occur.

From a practical perspective, the most significant risks in construction projects remain those related to resource constraints and cost escalation. This is confirmed by the results of the 2025 AGC survey conducted among construction firms and contractors (fig. 1).

Figure 1. *Key challenges faced by construction contractors according to the AGC 2025 survey (AGC, 2025)*



The results of the study emphasize that the task of automating risk management should be focused not only on identifying already occurred deviations, but also on predicting the likelihood of their occurrence under the influence of cost, time, resource, and organizational factors.

In this context, ML algorithms are important as a means of shifting construction risk management from a reactive to a predictive model (Hriday M. S.H. & Rehman A., 2025). Industry evidence shows that the sector is already moving in this direction: according to Deloitte, the share of construction companies in the Asia-Pacific region using artificial intelligence and ML increased from 26% in 2023 to 37%, while the average number of adopted digital technologies rose from 5.3 to 6.2 per company. In the United States, AGC reports that 44% of firms expect to increase investment in artificial intelligence, and the 2026 AGC survey shows its growing use in office applications, cost estimating, design, site monitoring, procurement, and scheduling. This indicates that ML-based risk automation already has a practical foundation and can be integrated into key construction processes.

Accordingly, the conceptual framework for automating construction risk management can be defined as the development of an intelligent system that processes schedule, cost, supply, productivity, quality, contractor, permitting, and external constraint data to generate risk probability estimates, classify events by criticality, and support preventive action. Within such a system, ML algorithms should address three main tasks: identifying hidden relationships among project parameters, predicting adverse events, and ranking risks by managerial priority.

Thus, the theoretical and methodological framing of construction risk management automation shows that ML should be treated not as an auxiliary digital tool, but as a core analytical mechanism for continuous risk identification, prediction, and prioritization. This creates the foundation for developing integrated risk-oriented systems capable of improving the timeliness, accuracy, and managerial value of decision-making in construction projects.

Comparative analysis of ML algorithms for predicting and ranking construction risks

The application of ML algorithms in construction risk management is primarily associated with the transition from descriptive and expert-based approaches to predictive data-driven analysis. In the literature, such algorithms are viewed as tools for identifying nonlinear relationships between project parameters, estimating the probability of adverse events, and supporting the selection of preventive management actions (Oduro S., 2025).

Table 2. *Comparative characteristics of ML algorithms for predicting and ranking construction risks*

Algorithm class	Typical tasks in construction risk management	Advantages	Limitations
Linear and logistic models.	Basic estimation of the probability of schedule and cost deviations. Primary risk classification.	High interpretability. Low data requirements. Ease of implementation.	Limited ability to capture complex nonlinear relationships.
Decision trees and ensemble models (Random Forest, XGBoost, LightGBM, boosting).	Ranking risk factors. Predicting schedule delays, accidents, and cost overruns.	High accuracy. Robustness to mixed features. Ability to assess feature importance.	Risk of overfitting. Need for hyperparameter tuning.
Neural network models and multilayer perceptrons.	Complex multiparameter prediction of quality, schedule, and cost outcomes.	Ability to detect hidden relationships. High performance on large datasets.	Lower transparency. Dependence on the quality of the training data.
Graph neural networks.	Modeling interconnected risks between participants, stages, and project nodes.	Good representation of the network nature of construction projects.	High complexity of implementation and data preparation.
Explainable AI models and SHAP-based analytics.	Interpretation of risk factors. Explanation of predictions for management purposes.	Increased trust in the model. Better applicability in decision-making.	Require an additional analytical layer.

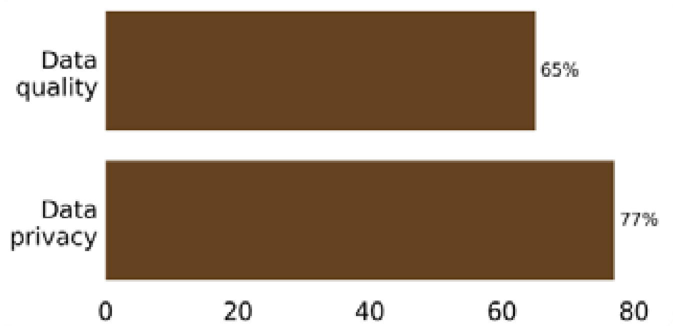
A systematic review of 84 peer-reviewed studies published between 2014 and 2024 identified five major artificial intelligence domains in construction risk management: ML, natural language processing, knowledge-based reasoning, optimization algorithms, and computer vision (Tian K., 2025). Among these, ML serves as the main predictive mechanism for modeling cost, schedule, safety, quality, and supply risks, making algorithm selection a key architectural component of automated risk analysis systems.

Considering the specific features of the management object, ML algorithms in construction risk systems should be selected based on the type of task, the nature of input data, and the requirements for result interpretability (table 2).

Empirical results from recent studies confirm that ensemble and neural network approaches demonstrate high practical potential in construction. For example, a 2025 study based on 1,015 projects and 499 defect categories reported that a multilayer perceptron achieved 94.1% accuracy in quality prediction and 98.4% in schedule status prediction, indicating the strong suitability of such models for early detection of deviations in key project parameters (Fan C. L., 2025).

At the same time, high accuracy alone does not ensure successful implementation. In construction risk management, interpretability, data quality, and integration into managerial processes are critical. The KPMG Q4 AI Pulse Survey (2025) indicates that data quality remains one of the key challenges for corporate AI adoption (fig. 2).

Figure 2. *Major barriers to scaling AI systems according to the KPMG Q4 AI Pulse Survey (KPMG, 2025)*



These findings indicate that in construction, priority should be given not merely to the most accurate models, but to algorithms that balance predictive performance, interpretability, and robustness to heterogeneous and imperfect project data. Therefore, a theoretically grounded system for construction risk automation should rely not on a single universal model, but on a set of coordinated algorithms, selected according to the type of risk, data quality, and the level of managerial decision-making.

Practical assessment of the effectiveness of algorithmic solutions in construction risk management: a comparative case analysis

The practical value of ML-based automation in construction risk management is most evident in real projects, where digital solutions function not as auxiliary analytics but as embedded elements of the operational management system. Corporate practice highlights several stable application areas, including the prediction of schedule deviations, prevention of defects and rework, mitigation of safety risks, automated monitoring of actual site conditions, and support for supply chain management. In the latter case, algorithmic tools help detect potential supply disruptions, anticipate shortages of critical resources, and reduce the transfer of logistics-related risks to project schedule, cost, and production performance (Miloserdov A., 2025).

Notably, despite differences in project profiles and implementation scales, a common pattern can be identified: algorithmic solutions shift risk management from a reactive response to consequences toward the early detection of deviations and timely intervention. Large construction projects, according to recent McKinsey analyses, often experience cost overruns of approximately 80% and schedule delays of around 50%, highlighting the critical importance of proactive risk management.

Practical implementation of algorithmic solutions in construction demonstrates that the greatest effect is achieved when ML methods are integrated into schedule control, defect prevention, and remote verification of actual site conditions. For example, **Suffolk Construction** applied the nPlan platform for AI-based risk management and forecasting in a hospital project in Boston. The case emphasizes the use of algorithmic forecasting for early identification of schedule risk zones and support of managerial decision-making during project execution (nPlan, 2024).

A representative example of artificial intelligence application in construction risk management is the case of **Nibbi Brothers General Contractors**, where AI-driven visual analytics within OpenSpace were used for early detection of discrepancies, prevention of rework, and reduction of coordination and cost-related risks. According to the company, this resulted in savings of $58,000 in travel costs, prevention of $63,000 in losses from a single rework incident, and elimination of $15,400 in billing discrepancies (OpenSpace, 2023). A similar effect was observed at **U. S. Engineering,** where the use of OpenSpace enabled savings of up to 10 hours per week through remote monitoring and earlier detection of deviations. These examples indicate that ML delivers the greatest value in construction when it is embedded not as an isolated analytical tool, but as part of a continuous system for preventing schedule, quality, and coordination risks.

As an additional example of a U.S. construction company applying ML to risk forecasting, the case of **JE Dunn Construction** using the Buildots platform is particularly relevant. In the published case, Buildots is described as being used for forecasting outcomes, data-backed delay mitigation, and improving execution control accuracy; notably, JE Dunn has already deployed the solution across projects totaling more than 3 million square feet. At the platform level, Buildots reports that its AI-powered progress tracking and delay forecasting can reduce delays by up to 50%, which makes this case relevant for analyzing machine-learning tools for schedule-risk prediction in construction (JE Dunn, 2025). At the same time, it should be noted that the publicly available JE Dunn case does not disclose company-specific before-and-after performance metrics, so the quantitative interpretation should be limited to the reported scale of deployment and the technology-level effect claimed by the platform.

Taken together, the reviewed cases show that the practical effect of ML in construction risk management is manifested not only in improved forecasting accuracy, but also in measurable reductions in rework, coordination losses, time expenditure, and schedule-related uncertainty. This suggests that the effectiveness of algorithmic solutions depends primarily on their integration into routine project control processes, where predictive analytics and AI-based monitoring can support earlier and more informed managerial intervention.

Discussion

The analysis shows that the effectiveness of ML in construction risk management depends less on adoption per se and more on how models are embedded into the project management workflow. The reviewed cases indicate that the greatest impact is achieved when algorithmic solutions address specific tasks – such as schedule deviation forecasting, rework prevention, reduction of coordination losses, and early detection of discrepancies between the design model and actual site conditions. At the same time, the results reveal limitations of a universal approach: some solutions are more effective in visual quality control, others in schedule risk prediction, while risks related to team coordination, subcontractor interaction, and supply chains require consideration of organizational dependencies, data exchange discipline, and logistical stability (Naidenova M., 2026). This suggests that ML cannot be treated as a standalone tool capable of uniformly addressing all categories of construction risks.

Equally important is the role of the organization's digital maturity. Fragmented data, lack of standardization, weak integration between project participants, and disconnections between planning, procurement, and site execution significantly reduce the practical value of even highly accurate models. In such conditions, algorithms may detect risks, but without the team's ability to interpret signals and translate them into timely actions in scheduling, procurement, or responsibility allocation, the managerial effect remains limited. Therefore, further development of ML-based risk management in construction should focus not only on improving model performance, but also on building integrated data environments where predictive analytics is embedded into team collaboration, supply chain coordination, and real-time decision-making processes.

Conclusion

Automation of construction risk management based on ML should be approached as the transition from periodic expert judgment to continuous predictive control of the project environment. The study shows that the object of automation is not an isolated risk, but an interconnected set of deviations related to schedule, cost, quality, safety, and contractual performance. For practical implementation, priority should be given to models that can both predict adverse events and rank risk factors by criticality. In this context, ensemble methods, neural network models, and interpretable analytical tools appear to be the most suitable options for construction projects, since they combine predictive capability with managerial usability.

The case analysis indicates that the greatest effect is achieved when algorithmic solutions are embedded into routine project processes rather than used as stand-alone analytical modules. In practice, this means that construction firms should integrate ML into schedule control, quality verification, site monitoring, and procurement coordination, while ensuring consistent project data and clear procedures for acting on model outputs. Thus, the most effective development path is the creation of integrated risk-oriented digital systems that combine prediction, monitoring, and response mechanisms. Further research should focus on industry-specific datasets, comparative validation of models across project types, and the development of implementation criteria linked to organizational scale and digital maturity.

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