

AI-Driven Decision Support for Project Risk Identification and Management Approach Selection

Idris A. Adelakun¹

¹ Assistant Teaching Professor, CISA - School of Applied Professional Studies, Arizona State University, USA

Correspondence: Idris A. Adelakun, Assistant Teaching Professor, CISA - School of Applied Professional Studies, Arizona State University, USA.

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Abstract

The underperformance of projects has become a major source of economic losses across various industries, and often, it is due to poor identification of risk and the mismatch between the nature of the project and management approach adopted. Conventional approaches to risk management are based on high levels of expert opinion and stand-still assessment tools and therefore can be restrictive in terms of consistency and scalability in complex organizational settings. This research paper presents a decision-support system using artificial intelligence (AI) that combines project risk identification with the selection of an appropriate project management approach. The framework is based on a structured design science approach and an applied case study that shows how an AI-generated risk profiling can help inform the choice of predictive, adaptive, or hybrid project delivery models. The results indicate that AI based planning leads to greater transparency and more effective strategic alignment during the initial stages of a project, while also helping to identify and mitigate potential subjective biases in decision making. The research paper also contributes to the current body of research on digital transformation in project governance and provides practical implications for enhancing organizational efficiency and project performance. Although the findings are provisional and based on a small number of case studies, the framework provides a basis for future empirical validation across various industries.

Keywords: artificial intelligence, project risk management, decision support system, organizational performance, hybrid project management

1. Introduction

Projects have operational environments that are uncertain, technologically disruptive, regulated and changing stakeholder expectations. Regardless of decades of the methodological improvement, the level of project failure is quite high in industries. Excessive costs, time delays and under-performance are major economic costs to organizations. It has been found out that the conventional notions of risk are narrow and that risk management practices are not being fully exploited or aligned with project requirements. Software projects are diverse in structure, and formal project management does not always guarantee success. Furthermore, research and practice are not always in alignment with actual project needs (Bannerman, 2008).

Conventional project risk management framework, including PMBOK ® Guide for project management and ISO 31000:2018, place a significant emphasis on systematic identification, analysis, and response planning. Nevertheless, these models rely heavily on the use of expert judgment, brainstorming, and static checklists of Project Management Institute (PMI, 2021; ISO, 2018). As useful as they are, these methods might not scale or be consistent in a variety of project settings which are data intensive.

Previous studies have shown that the nature of projects plays a major role in the effectiveness of the management strategies adopted, but most organizations still rely on habitual or standardized strategies rather than systematic contextual alignment.

Artificial intelligence (AI) has the potential to enhance managerial decision-making by identifying trends in project data and enabling systematic analysis. Although the use of AI in forecasting and analytics is increasing, there is a paucity of research that integrates AI-driven risk identification with methodology selection into a single decision-support system.

This paper fills this gap by proposing and intuitively justifying an AI-enabled framework that combines risk

identification in a project with the selection of a project management approach. It aims to investigate the potential of AI-assisted analysis to make the process of early-stage planning of projects more transparent, consistent, and cost-efficient.

1.1 Objectives of the Study

The main aim of the present work is to design and test an artificial intelligence (AI)-based decision-support system that combines project risk identification with the choice of project management method in an organizational setting.

More precisely, the research is aimed at:

1. Analyzing the weaknesses associated with conventional risk identification and methodology selection in project management.
2. Designing a structured AI-based system to enhance transparency and consistency in early-stage project planning.
3. Demonstrating how a project's risk profile can inform decisions regarding predictive, adaptive, or hybrid project management approaches.
4. Evaluating the organizational and economic impact of adopting AI-based decision support in project governance processes.

1.2 Project Risk Identification in Organizational Context

Effective project governance is based on risk identification. Standardized systems focus on the systematic identification of uncertainties that can influence the project goals (PMI, 2021; ISO, 2018). The most widespread methods are expert judgment, brainstorming, Delphi methods, and SWOT analysis (Ullah et al., 2024).

Bannerman (2008) however asserts that the risk management practices do not tend to adapt to the diversity of the project especially when it comes to software and innovation intensive environments. De Bakker et al. (2015) also emphasize that risk management fulfills not only analytical roles in organizations but communication and governance as well.

The recent studies investigated data-based risk identification with the help of predictive analytics and machine learning (Bauskar et al., 2024). The approaches can be used to show the possibility of finding the latent risk patterns in textual documentation and historical project records (Ferhati et al., 2025). However, there is a limited involvement in the managerial decision making.

1.3 Project Management Approach Selection

The differences among predictive, adaptive and hybrid approaches to project management are set upon diverse assumptions on the stability, complexity and stakeholder engagement on project management (PMI, 2017; Gustavsson, 2016). Predictive methods focus on long term planning and the execution in a sequence in relatively steady conditions. Adaptive strategies, on the other hand, favor the iterative development and responsiveness to changing needs. Hybrid models combine formal structures of governance and adaptive flexibility in response to mixed project environments.

The significance of contextual alignment in the choice of methodology has been placed more and more in the focus of scholars. Cicmil et al. (2006) argue that project complexity is socially constructed, and methodological rigidity can be an inadequate means of reflecting organizational realities. In the same vein, Geraldi et al. (2011) define complexity as multidimensional in nature which includes structural, uncertainty-related and socio-political dimensions. Serrador and Pinto (2015) go a step further to show empirically that the success of a project is highly related to the fit between the project characteristics and management approach adopted.

Notwithstanding these observations, the choice of approach, in practice, is frequently determined by institutional routines, organizational culture or even the whim of the managerial as opposed to systematic contextual evaluation. This detachment implies that there is a need to introduce systematic decision-support systems that can transform project risk profile into evidence-based methodology recommendations.

1.4 Artificial Intelligence for Managerial Decision Support

Project management applications of artificial intelligence (AI) and machine learning (ML) are beginning to be used to help managers make decisions. These technologies assist in a number of essential processes, such as the identification of risks, the choice of project management methods, forecasting, and resource allocation (Reznikov, 2025; Dukhram Pal et al., 2023). By analyzing extensive amounts of past and present project data, AI systems can detect trends that may be difficult to identify using traditional analytical tools. According to recent research, ML models can enhance the accuracy with which projects costs and schedules are predicted. The fact that these models can determine the complex relationship in datasets means that they give managers more credible information to guide them in planning and making initial decisions (Johnson, 2023; Narbaeva et al., 2023). Moreover, textual project documentation has been analyzed through Natural Language Processing (NLP) techniques and transforming unstructured information to structured

numerical data. The process facilitates the inclusion of project information in data-driven management systems and helps to conduct a more formal analysis when planning the project (Di Giuda et al., 2019).

Nevertheless, most recent AI solutions are still rather task-specific, like predicting costs or analysis of sentiments instead of offering holistic advice in the project lifecycle (Shamim et al., 2025). Consequently, there is an increasing demand of combined AI systems that would include risk identification and offer recommendations on appropriate project management strategies such as predictive, adaptive, or hybrid models. This integration would make a great contribution to managerial decision-making and the project results.

An incremental implementation practice might be the most feasible to deploy AI for companies that want to implement it. Firms can start with the implementation of AI in the critical domains, like automated risk detection or data-driven suggestions in the choice of project management strategies. The gradual integration will enable teams to assess the usefulness of these technologies, adapt the workflows, and limit the interference to the current processes. Such a gradual strategy can in the long run facilitate greater usage of AI and reinforce decision-making at initial phases of planning the project and its alignment with the organizational goals (Reznikov, 2025).

1.5 Research Questions

The research questions that are to be answered in this study are:

RQ1: What possibilities are there to use AI-assisted analysis to identify systematic project risk?

RQ2: What are the ways in which AI generated risk profiles can be used in the selection of project management approach?

RQ3: Which organizational consequences can be identified in the context of the implementation of AI in planning of early project stages?

2. Method

2.1 Research Design

In the present research, a Design Science Research (DSR) approach is applied to create and test an AI-based decision-support model of risk identification in the project and the selection of approach to manage project risks. DSR suits the purpose of the research that would develop innovative artifacts to solve identified organizational issues and make contributions to theoretical and practical knowledge.

In contrast to the purely explanatory research, DSR deals with the systematic design, development, and evaluation of artifacts that should be aimed at enhancing managerial practice. The artifact created during this research is a systematic AI-supported framework, which incorporates risk identification, risk scoring, and methodology recommendation into one decision-support process.

The DSR process had five fundamentals stages:

- (1) Problem identification
- (2) Objective definition
- (3) Design and development of artifacts
- (4) Demonstration
- (5) Evaluation.

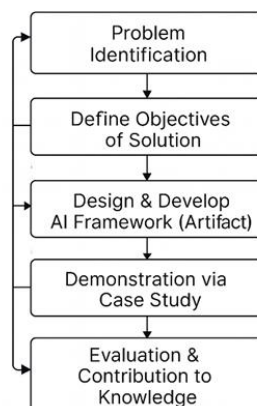


Figure 1. Design Science Research Process Applied in this Study

2.2 Problems and Objective Identification

The issue addressed in this study is the lack of a systematic approach to integrating project risk identification with the selection of a project management approach. Predictive, adaptive or hybrid methodologies are often chosen at the subjective level and through organizational habit by the organizations, many of whom do not formally align their choice to risk characteristics of a project.

The proposed solution strategy aims at creating a decision-support architecture by:

- Identifying the project risks in several categories in a systematic way.
- Organizing rating of risks with probability-impact scoring.
- Mapping risk profile to right management strategies.
- Giving clear justifications of recommendations.

The next stage in the model design cycle is artifact design and development.

2.3 The Artifact Design and Development

The main artifact that was created during this research is an AI-based decision-support architecture. The framework also combines structured project input analysis with risk categorization criteria, scoring logic and methodology alignment criteria.

The artifact itself is made up of three incorporated parts:

- Risk Identification Module

Identifies and categorizes risks in technical, financial, regulatory, operational and stakeholder areas.

- Risk Assessment Module

Ranks risks using a systematic likelihood-impact scoring system.

- Methodology Recommendation Engine

To predict risk management with rule-based decision logic, risk characteristics were mapped and consolidated into predictive, adaptive or hybrid management approaches.

The artifact would facilitate the increase of transparency, lessen subjective bias, and offer scalable governance assistance across organizational portfolios.

2.4 Exhibition: Case Practice

The framework was used with a structured case study: The Patio Brick Pizza Oven Design Project to prove the functionality of the artifact. The case involved scope, stakeholder expectations, regulatory factors, and budget limitation as well as environmental uncertainties.

The AI-supported framework created an ordered risk register, risk scores, and mitigation solutions and suggested a hybrid project management model relying on the combined risk profile.

This pilot testing showed how the artifact can be used in a real-world project planning context.

2.5 Evaluation Strategy

Design Science Research evaluation enables researchers to determine whether the artifact is an effective solution to the identified problem. In this study, the evaluation was conducted by:

- Logical consistency analysis
- Alignment with established project management literature
- Case-based validation of risk detection completeness
- Coherence between risk profile and methodology recommendation

The findings tentatively confirm the hypothesis that the artifact enhances the structured decision-making process when the project is at initial stage planning. However, empirical validation of the research in several projects and industries should be carried out in the future to enhance generalizability.

3. Results and Discussion

3.1 General Overview of Artifact Demonstration

The AI-assisted decision-support framework was applied to the Patio Brick Pizza Oven Design Project to evaluate to determine its ability to (1) systematically determine the risks and (2) provide a recommendation based on aligned

project management approach. The demonstration aimed at evaluating the viability of the artifact to generate structured, transpired and logically consistent results in line with known project management theory.

The system took structured project inputs such as the scope definition, environmental constraints, stakeholder involvement, budget consideration and regulatory requirements as well as, the complexity of executing the project. Using these inputs, the framework produced categorized risk register, probability-impact scores, recommended mitigation strategies and a methodology of management.

The obtained results are presented in two sections: (1) risk identification and scoring results, and (2) methodology recommendation and logic of alignment.

3.2 Identification and Scoring of Risk Generated by AI

The framework observed several risks categories such as:

- Design inaccuracies
- Material availability delays
- Budget overruns
- Construction quality issues
- Regulatory compliance risks
- Environmental and weather-related constraints
- Stakeholder communication breakdowns
- Client approval delays

The likelihood-impact model of a five-point scale was used to assess each of the identified risks. The risk scores were obtained as a product of the probability and impact rating, which generated a priority (e.g., high, medium).

Table 1. Output Risk Assessments AI Generated

Risk	Probability	Impact	Score	Level	Mitigation & Recommended Approach
Design Inaccuracy	4	4	16	High	Conduct regular design reviews (Agile)
Material Availability Delay	3	4	12	Medium	Secure multiple suppliers (Hybrid)
Budget Overruns	3	5	15	High	Allocate contingency reserve (Agile)
Construction Quality Issues	3	5	15	High	Perform routine quality inspections (Agile)
Regulatory Compliance Issues	2	5	10	Medium	Early consultation with authorities (Hybrid)

The grading session was organized in a way that made the results scoring results highly valuable.

3.2.1 Risk Transparency and Prioritization

The scoring technology created by AI allowed the prioritization of risks to be made explicit. As an example, design errors and construction quality were rated as part of the high composite scores because of high probability and high impact. The priority facilitates oriented managerial focus and specific mitigation planning.

Contrary to classical risk identification methods that rely on brainstorming, which may not be properly prioritized, the framework ensures that each identified risk is rated consistently based on established criteria. This minimizes cognitive bias and inconsistency among project teams.

3.2.2 Correspondence of Mitigation Strategy

The model did not only name risks but also came up with mitigation suggestions. For example:

- Iterative review cycles were associated with high design uncertainty risks.
- The contingency reserve allocation was associated with budget volatility risks.
- There were regulatory risks associated with pre-compliance consultation schemes.

This hierarchical connection of risk identification and response plans increases the coherence of governance and helps to manage proactively, not reactively.

3.2.3 Theoretical Alignment

The risk categories created by the system are highly correlated with the identified risk domains found in the literature of project management such as technical, financial, operational, and regulatory dimensions. This correspondence implies that the artifact generates outputs that are in line with the available theoretical perspectives to enhance construct validity.

Taken together, these results support the Research Question 1:

RQ1: What possibilities are there to use AI-assisted analysis to identify systematic project risk?

The findings suggest that AI-assisted processing has the potential to produce detailed, organized, and prioritized

3.3 Recommendation of AI-Generated Methodology

After aggregation and prioritization of risks, the framework assessed the project risk profile as a whole and provided a recommendation of a hybrid project management strategy.



Figure 2. Recommendation Output of AI-Generated Methodology

The systematic rationale generated by the system is illustrated in Figure 2, where the identified regulatory risks are connected to design risks, and the degree of uncertainty in the construction phase is aligned with adaptive practices.

This suggestion correlates with the literature that underlines other-based selection of methodology (Conforto et al., 2016). The RQ2 is supported in the case in an exploratory manner.

The recommendation came on the basis of aggregate indicators which comprised:

- Moderate design uncertainty
- Regulatory compliance constraints
- Execution-phase environmental variability
- Stakeholder involvement requirements

The system suggested a hybrid approach that involves a predictive approach to planning during the design and compliance phases and an adaptive approach during construction and implementation.

3.3.1 Logical Consistency of Recommendation

The identified risk profile is internally logically consistent with the hybrid recommendation. Regulatory compliance risks tend to be associated with structured documentation and step-by-step controls (predictive factors). Adaptive responsiveness (agile elements) is supported by environmental and material variability in the process of construction. This moderate suggestion is consistent with the literature, which indicates that hybrid models are especially suited to environments that are either mixed (in terms of levels of uncertainty) or moderate (in terms of complexity).

3.3.2 Integration of Risk and Governance Decisions

One of the major contributions of the artifact is the combination of risk assessment with the selection of the governance structure. Conventionally, risk management and choice of methods are considered two distinct managerial choices. The framework fills this gap by establishing a connection between the characteristics of risks and structural project design decisions.

This incorporation answers Research Question 2:

RQ2: What are the ways in which AI-generated risk profiles can be used to select the project management approach?

The results show that risk aggregation has the potential to be a rational basis of the choice between predictive, adaptive, and hybrid methods and enhances the methodological consistent.

3.4 Implications to Organizations

The framework has more than technical functionality implications on an organization.

3.4.1 Reduction of Subjective Bias

This method minimizes errors that a subject can make in relation to the artifact. This approach reduces the number of mistakes a subject may make in relation to the artifact. Experience-based heuristics, political processes, and the influence of the dominant stakeholders are the usual factors that impact the traditional risk workshops. Using common scoring and logic principles, the framework increases objectivity and consistency among the projects.

3.4.2 Scalability at a Portfolio Level

Since the framework has the structured inputs, it is scalable to several projects in a portfolio. This would allow stable standards of governance and enhance comparability among initiatives.

3.4.3 Knowledge retention and Institutional Learning

The hierarchical system of AI-assisted outputs generates documentation that can be stored and compared between projects. This could help to improve organizational learning in the long run and provide better predictions of risks in the future.

3.5 Economic Implications

Underperformance of the project often leads to:

- Cost overruns
- Schedule delays
- Rework expenses
- Opportunity costs

The framework can lead to economic efficiency in a number of ways by:

- Minimized rework through early detection of design risks.
- Enhanced resource distribution by methodology correspondence.
- Reduced compliance-related fines.
- Better forecasting of schedules.

Although the research is currently not conducted on quantitative financial modeling, the logical connection between enhanced planning fit and economic performance postulates that there is a high possibility of a return on investment on organizations implementing these systems.

3.6 Design Science Perspective Evaluation

In the Design Science Research, the question of evaluation is whether the artifact can be effective to tackle the articulated problem.

The demonstration of the case shows that the framework:

- Was able to create a complete risk register.
- Consistent scoring logic being applied.
- Developed a methodology advice in line with risk characteristics.
- Gives clear explanatory rationale.

The artifact has functional validity and conceptual coherence though it was built on a single case study. Widespread testing of industries would also increase the extent of generalizability.

3.7 Synthesis of Findings

The aggregate findings are integrated in support of the research questions of the study:

The systematic risk identification is improved by AI-assisted analysis (RQ1).

Aggregated risk can be used to inform methodology selection (RQ2).

There are significant organizational and economic implications (RQ3) of the integration of AI in project planning.

The results place AI as an augmentation mechanism, rather than a replacement of managerial judgment, which enhances structure, transparency, and quality of decisions.

4. Conclusion

This paper dealt with one of the long-standing problems of poor coordination between project risk identification and project management methodology selection. Although the methods of risk management have been well developed, the choice of either predictive, adaptive, or hybrid approach is often based on subjective judgement and organizational culture. This disconnection leads to project underperformance, cost overruns and governance inefficiencies.

The proposed research method employed Design Science Research which has made it possible to create and demonstrate an AI-based decision-support framework combining structured risk identification and probability-impact scoring with methodology recommendation in a single artifact. The case-based evaluation reveals that the framework has the potential to produce complete risk registers, rank them in a systematic manner and provide recommendations on the project management approaches that are logically aligned.

The results give preliminary evidence to three important lessons:

- The use of AI to aid in the analysis may also increase the transparency and consistency of project risk.
- Methodology can be chosen based on rational criterion of aggregated risk profiles.
- It can be proposed to enhance the quality of decisions made in organizations and the transparency of governance by integrating AI into the early-stage planning processes.

Theoretically, this study contributes to research on digital transformation in project governance by demonstrating how AI-driven artifacts can bridge the gap between analytical risk assessment and methodological decision-making. It also contributes to Design Science Research literature by introducing and evaluating an artifact that integrates risk analytics with governance recommendations.

In practical terms, the framework provides organizations with a scalable mechanism to minimize subjective bias, improve consistency at the portfolio level and possibly, increase economic outcomes by aligning management strategies with contextual project risks.

5. Limitations and Future Research

Despite its contributions, this study has a number of limitations. First, the analysis is based on a single illustrative case study, the “Pizza Oven” project. While suitable for the preliminary demonstration of Design Science Research, its simplicity limits the generalizability of the findings to more complex industrial projects. Future research should apply the framework to high complexity projects across multiple industries to validate its applicability.

Second, the input data of the project is important because it determines the quality and completeness of the framework. The quality of project description can have an impact on the correctness of risk identification and reliability of recommendations.

Third, the research lacked the assessment of quantitative performance and the longitudinal outcome. Future studies ought to evaluate the hypothesis of whether AI-assisted methodology alignment generates any statistically significant change in cost management, scheduling compliance, or stakeholder satisfaction.

The future research should thus:

- Apply the framework across diverse industries and project types
- Conduct comparative analysis against traditional risk workshops
- Incorporate empirical performance metrics
- Explore integration with enterprise project portfolio management systems

These extensions would also justify the economical and organizational worth of AI-aided decision-support in the project governance.

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Author contributions

Dr. Adelakun was responsible for the study design, data collection, analysis, and the drafting and revision of the manuscript, following a design science research approach. The author read and approved the final manuscript.

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Data sharing statement

No additional data are available.

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