*Quest Journals*
*Journal of Research in Business and Management*
*Volume 14 ~ Issue 10 (October 2026) pp: 25-31*
*ISSN(Online):2347-3002*
www.questjournals.org

**Research Paper**

# Project Management in the AI–Quantum Era: A Hybrid Framework for Prediction, Optimization, and Risk Control

Jason Liu[1], Calvin Chen[2], Eli Aba[2]
[1,2] *(Department of Operations and Management, University of Wisconsin-Stout Polytechnic)*
*Corresponding Author: Jason Liu*

***ABSTRACT:*** *Artificial intelligence (AI) is reshaping project management by expanding the use of predictive analytics, automated information processing, adaptive scheduling, and data-supported risk analysis. Quantum computing adds a different computational proposition: selected optimization problems may be represented and explored through hybrid quantum–classical procedures rather than conventional search alone. This article develops a critical framework for considering these technologies together in project environments. Instead of treating quantum artificial intelligence (QAI) as a proven replacement for established project controls, the study distinguishes capabilities that are currently practical from those that remain experimental. Three infrastructure cases— the Channel Tunnel, the Sydney Opera House, and Boston's Big Dig—are used as retrospective stress cases for cost escalation, schedule disruption, resource constraints, and interdependent risk. A simulation-oriented comparison of traditional project management (TPM), AI-enabled project management (AI-PM), and QAI-enabled project management (QAI-PM) is retained as an exploratory scenario analysis rather than evidence of historical counterfactual performance. The resulting framework positions AI as the near-term decision-support layer and hybrid quantum–classical optimization as a research layer for difficult combinatorial problems. The paper concludes that QAI has strategic potential, but credible adoption requires transparent baselines, reproducible experiments, realistic hardware assumptions, human oversight, and direct comparison with strong classical optimization methods.*

*Received 07 Oct., 2026; **R**evised 16 Oct., 2026; **A**ccepted 18 Oct., 2026 © The author(s) 2026.*
***P**ublished with open access at **www.questjournals.org***

## I. INTRODUCTION

Project management increasingly operates in settings where schedules, resources, stakeholder expectations, technical constraints, and uncertainty interact continuously. Traditional tools such as critical-path analysis, Gantt schedules, risk registers, and deterministic cost baselines remain valuable, but they were not designed to learn automatically from high-volume data or repeatedly recompute decisions as conditions change. AI-enabled project management extends these practices by adding forecasting, classification, natural-language processing, anomaly detection, and optimization. Recent systematic reviews show growing interest in AI across project planning, monitoring, uncertainty management, construction, and information-technology contexts (Taboada et al., 2023; Hashfi & Raharjo, 2023; Salimimoghadam et al., 2025).

A second technological trajectory is quantum computing. For project management, its most relevant promise is not general "faster computing," but the possibility that particular optimization formulations may benefit from quantum or quantum-inspired search. The Quantum Approximate Optimization Algorithm (QAOA), for example, targets combinatorial optimization, while variational quantum approaches combine parameterized quantum circuits with classical optimization. Contemporary evidence nevertheless emphasizes hardware noise, connectivity, circuit depth, precision, and benchmarking as consequential limitations (Callison & Chancellor, 2022; Weidenfeller et al., 2022; Blekos et al., 2024). Thus, claims of immediate project-management superiority should be separated from research hypotheses about future advantage.

Accordingly, this study addresses a focused question: how can AI and hybrid quantum–classical computation be incorporated into project decision architectures without overstating present capability? This article makes three contributions. First, it reframes TPM, AI-PM, and QAI-PM as complementary maturity layers rather than mutually exclusive replacements. Second, it interprets three megaproject cases as stress

scenarios for evaluating decision requirements. Third, it proposes an evidence-oriented validation roadmap that distinguishes observed historical facts, classical simulations, and quantum experiments. The analysis is guided by two research questions: (RQ1) Which project-management decision tasks are currently suitable for AI-enabled prediction and decision support? (RQ2) Under what conditions could hybrid quantum-classical optimization be meaningfully benchmarked for project scheduling, resource allocation, and risk-response problems?

## II. SYSTEM COORDINATES

AI contributes most directly when project data can be converted into repeatable prediction or decision tasks. Machine-learning models can support forecasting, classification, risk prioritization, schedule assessment, or resource recommendations, while generative systems can assist with knowledge retrieval and project communication (Aliyev, 2025). Empirical and review literature also warns that benefits depend on governance, data quality, human expertise, integration, and organizational adoption (Felicetti et al., 2024; How & Cheah, 2024; Salimimoghadam et al., 2025). AI should therefore be viewed as an augmentation mechanism embedded in project controls, not as an autonomous substitute for accountable project leadership.

Quantum computing addresses a different computational layer. QAOA and other variational algorithms are designed around optimization landscapes that can be encoded into objective functions or Hamiltonians. Vogel (2011) reviewed Nielsen and Chuang's foundational text on quantum computation and quantum information (see Figure 1). Reviews of QAOA report a broad research base but also emphasize that useful quantum advantage is problem- and hardware-dependent (Blekos et al., 2024). Hardware studies show that mapping, fidelity, execution time, and sampling can materially affect practical performance (Weidenfeller et al., 2022). More recent work further demonstrates that precision errors can degrade QAOA performance, reinforcing the need for careful experimental controls (Quiroz et al., 2025).

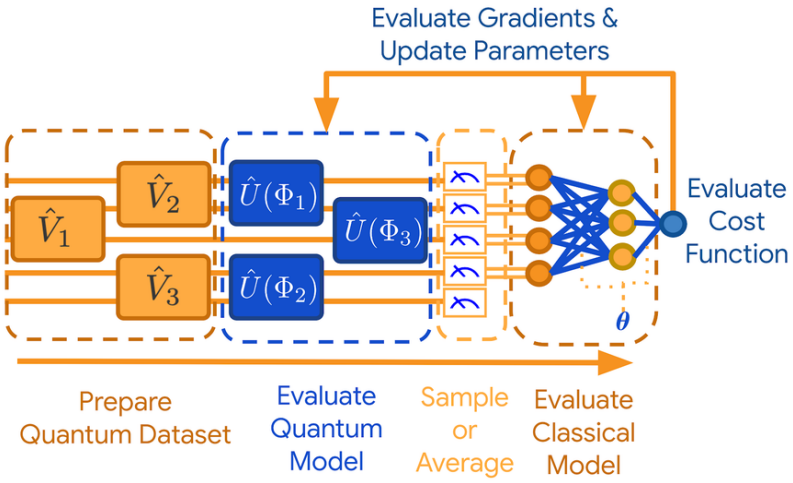



**Figure 1.** Ilustrative hybrid quantum-classical data-evaluation workflow (Aliyev, 2025)

Hybrid architectures are especially relevant because present quantum processors do not operate independently of classical computation. In a hybrid workflow, classical systems prepare data, formulate the optimization problem, update parameters, and interpret outputs, while a quantum processor performs a specialized subroutine. Callison and Chancellor (2022) argue that such hybridization is likely to remain important beyond the noisy intermediate-scale quantum period. For project management, this suggests a pragmatic architecture in which conventional project information systems remain the operational backbone, AI provides prediction and decision support, and quantum routines are invoked only for rigorously defined optimization subproblems.

The distinction between capability and evidence is essential. QAI is frequently discussed in finance, industrial optimization, digital twins, and other complex settings, but transfer to project management cannot be assumed automatically. Recent work on quantum machine learning and quantum-enabled optimization points to expanding application areas while continuing to identify data encoding, hardware, scaling, and validation challenges (Gujju et al., 2023; Winker et al., 2023; How & Cheah, 2024). Accordingly, this study treats QAI-PM as an experimental research framework whose value must be benchmarked against classical alternatives.

## III. METHODOLOGY

TPM provides the governance baseline. It structures scope, work packages, milestones, dependencies, budgets, and risks through transparent rules and human judgment. Its strength is interpretability and established organizational practice; its weakness in highly dynamic settings is that models may require manual updating and may represent uncertainty simplistically. AI-PM adds a learning layer. Historical and real-time data can be used to estimate delay probability, forecast cost pressure, flag anomalies, identify resource conflicts, or recommend revised schedules. This layer is adaptive but not automatically trustworthy: model drift, incomplete records, biased training data, opaque outputs, and automation overreliance can undermine decisions. Effective implementation therefore requires audit trails, uncertainty reporting, domain review, and a clear distinction between prediction and authorization. QAI-PM adds an optimization research layer. Project scheduling and resource allocation can often be represented as constrained combinatorial problems. A candidate quantum workflow translates decision variables and constraints into a suitable mathematical representation, executes a quantum or hybrid routine, and compares the resulting solution with classical solvers under equivalent conditions. Quantum parallelism should not be interpreted as evaluating every project plan and returning a perfect answer. Rather, quantum algorithms manipulate probability amplitudes under a specific circuit design, and any claimed advantage must be demonstrated through comparative benchmarks .

This study adopts a conceptual, case-based, and simulation-oriented design. Evidence is organized into four categories: (1) peer-reviewed literature on AI-enabled project management; (2) recent literature on quantum optimization and hybrid algorithms; (3) publicly documented megaproject cases; and (4) exploratory simulations that illustrate how alternative decision models could be compared. This structure improves traceability by preventing simulated outputs from being presented as observed historical outcomes. the Channel Tunnel, the Sydney Opera House, and Boston's Big Dig are reexamined because they expose different forms of project complexity: schedule slippage, cost escalation, technology integration, organizational coordination, labor disruption, and uncertainty. Historical case information establishes the problem context. It does not establish what AI-PM or QAI-PM would actually have achieved if deployed retrospectively. Counterfactual improvements are therefore interpreted only as scenario assumptions to be tested, not factual savings.

Monte Carlo analysis can represent variability in cost and duration by repeatedly sampling from specified distributions. FMEA provides a structured method for prioritizing failure modes through the risk priority number $RPN = S \times O \times D$, where severity, occurrence, and detection are scored according to an explicitly documented rubric. In the redesigned framework, the distributions and FMEA scores should be subjected to sensitivity analysis because results are conditional on those inputs. Reproducibility also requires publication of random seeds, parameter values, solver settings, and source data.

For quantum experiments, a fair comparison requires identical objective functions and constraints across methods. QAOA should be compared not only with TPM but with strong classical optimization baselines. Hardware topology, shot count, optimizer, circuit depth, noise model, execution time, feasibility rate, optimality gap, and solution stability should be reported. Such benchmarking follows directly from contemporary QAOA research, which shows that practical results can be sensitive to hardware and implementation choices (Weidenfeller et al., 2022; Blekos et al., 2024; Quiroz et al., 2025).

## IV. DATA ANALYSIS, RESULTS AND DISCUSSION

### 4.1 Data

**Case study: The Channel Tunnel**

The Channel Tunnel, commonly known as the Chunnel, is a major transportation megaproject connecting Folkestone in the United Kingdom with Coquelles near Calais in France through approximately 50 kilometers of tunnel beneath the English Channel. Officially opened in 1994, the project established the only fixed transportation link between Great Britain and continental Europe. It was financed entirely through private-sector capital and represented one of the most ambitious privately financed infrastructure projects undertaken at the time. Despite its engineering achievement, the Channel Tunnel experienced substantial financial difficulties. The project was originally estimated to cost approximately £4.8 billion in 1985, but its total cost reached about £9.5 billion by the end of construction. This represented an estimated real-term cost overrun of approximately 80%. Delays associated with construction, equipment delivery and testing, together with safety-related design modifications during construction, contributed significantly to the increase in expenditure (Global Infrastructure Hub, 2025). The project's complexity was further increased by the involvement of two national governments, financial institutions, contractors, regulatory agencies, and other stakeholders. Construction also involved significant technological and geological uncertainties. Project Management Institute analysis describes how unexpected conditions, stakeholder-requested changes, and technological requirements resulted in substantial

modifications during implementation. Ultimately, the tunnel was completed late and over budget, illustrating the importance of realistic forecasting, risk management, requirements management, and stakeholder coordination in international megaprojects (Anbari et al., 2008).

**Case study: The Sydney Opera House**

The Sydney Opera House provides another prominent example of the challenges associated with managing an innovative and highly complex project. Construction began in 1959 with an ambitious four-year schedule and an estimated budget of approximately AU$7 million. However, the building did not open until 1973. Its final cost reached approximately AU$102 million, representing a cost overrun of 1,357% and completion approximately ten years later than originally scheduled ("Sydney Opera House," 2019). A major source of difficulty was commencing construction before the design and engineering requirements had been sufficiently developed. According to the Project Management Institute, the project had relatively few completed drawings when foundation construction began. The innovative shell-shaped roof also created unprecedented engineering challenges, and a workable approach for constructing the shells was not developed until 1961. In addition, incomplete plans, stakeholder disagreements, and leadership changes complicated subsequent phases of the project. Although the project performed poorly against its original cost and schedule objectives, its ultimate outcome demonstrates that megaproject success cannot always be evaluated solely in terms of adherence to the initial budget and schedule. The Sydney Opera House subsequently became an internationally recognized cultural and architectural landmark. From a project-management perspective, the case particularly demonstrates the risks associated with premature construction, incomplete requirements, uncertain scope, technological innovation, and inadequate coordination between design and execution ("Sydney Opera House," 2019).

**Case study: Boston's Big Dig**

Boston's Central Artery/Tunnel Project, widely known as the Big Dig, was one of the most ambitious urban transportation projects undertaken in the United States. The project involved replacing Boston's elevated Central Artery with an underground expressway, extending Interstate 90 toward Logan International Airport, constructing new tunnels and bridges, and transforming land previously occupied by elevated highway infrastructure. Construction was carried out largely during the 1990s and 2000s, with the overall project concluding in 2007 (Wikipedia contributors, 2026).

**4.2 Data Analysis**

The Big Dig became particularly notable for its substantial cost escalation and schedule problems. The project was originally expected to be completed in 1998 at an estimated cost of approximately $2.8 billion. Instead, it was completed in December 2007 at a reported project cost of approximately $14.6 billion. In addition to financial and schedule difficulties, the project encountered engineering problems, leaks, design deficiencies, construction-quality concerns, and disputes over project execution. Managing construction within a densely developed urban environment contributed to the project's complexity. At the same time, the project ultimately delivered significant physical changes to Boston's transportation and urban infrastructure, including underground highway facilities, the Zakim Bunker Hill Bridge, the Ted Williams Tunnel connection, and the Rose Kennedy Greenway created in areas previously occupied by the elevated roadway. The Big Dig therefore provides a valuable project-management case for examining cost estimation, risk identification, quality control, contractor oversight, stakeholder management, and governance in extremely complex infrastructure programs (National Audit Office and other authoritative project records)

Channel Tunnel illustrates why large projects require integrated schedule, cost, systems, and stakeholder information. The historical record shows substantial cost escalation and schedule disruption during delivery. These figures provide historical context, whereas estimated improvements under TPM, AI-PM, and QAI-PM are treated as counterfactual scenario outputs rather than observed outcomes. A defensible AI experiment would train forecasting models on data available at defined decision points and evaluate whether they improve calibration or early-warning performance. A defensible quantum experiment would isolate a bounded scheduling or resource-allocation problem and compare solution quality against classical solvers.

Boston's Big Dig offers a second stress case involving long duration, dense urban construction, interfaces among organizations, and substantial cost growth. Monte Carlo distributions were used to estimate conditional cost and duration outcomes under the three management approaches. Those simulations are useful pedagogically, but their parameter choices determine the outcome. The stronger research design is to publish those assumptions, run sensitivity tests, and treat the resulting differences as conditional scenarios. AI could

then be evaluated for prediction quality, while QAOA or another quantum optimizer could be tested on a specific resource or sequencing formulation.

The Sydney Opera House case emphasizes systemic risk rather than computational difficulty alone. Inflation, labor disruption, design complexity, deadline pressure, and governance problems demonstrate that some project failures cannot be solved merely by better optimization. FMEA can help structure such risks, and AI may improve early detection where reliable data exist. Quantum optimization may contribute when the response problem contains a difficult combinatorial allocation or sequencing component, but it cannot substitute for stakeholder governance, contracting strategy, leadership, or institutional accountability.

### 4.3 Results and Interpretation

The analysis yields a central conceptual finding: technological value increases when each method is assigned to the problem it can credibly address. TPM remains necessary for governance, baselines, accountability, and transparent control. AI-PM is well suited to data-rich prediction and adaptive decision support. QAI-PM is most appropriately treated as an optimization experiment for carefully bounded, high-complexity subproblems. This layered view is consistent with the growth of AI-enabled project management research (Taboada et al., 2023; Felicetti et al., 2024; Salimimoghadam et al., 2025) and with the continuing emphasis on hybrid computation in quantum research (Callison & Chancellor, 2022).

The scenario analysis indicates potentially substantial reductions in delay, risk, and resource inefficiency under the specified QAI-PM assumptions. Those values should not be interpreted as evidence of quantum advantage because they arise from assumed distributions and modeled scenarios rather than controlled deployment of quantum project-management systems. The scientifically supportable conclusion is therefore more cautious: the scenarios illustrate hypotheses worth testing. Demonstrating superiority would require matched benchmarks, real project datasets, transparent model assumptions, statistical uncertainty, and comparison against optimized classical methods.

This reinterpretation also changes how scalability is discussed. Classical AI can scale effectively for many predictive tasks, while quantum hardware currently faces nontrivial operational constraints. QAOA research reports both algorithmic promise and implementation barriers, including connectivity, fidelity, noise, runtime, sampling burden, and parameter precision (Weidenfeller et al., 2022; Blekos et al., 2024; Quiroz et al., 2025). Consequently, "quantum scalability" should be evaluated empirically for a defined problem rather than asserted as a general property.

***Table 1**. Evidence-oriented comparison of project-management approaches*

| Dimension | TPM | AI-PM | QAI-PM |
|---|---|---|---|
| Primary role | Governance, planning, baseline control | Prediction and adaptive decision support | Experimental combinatorial optimization |
| Typical inputs | Plans, estimates, dependencies, expert judgment | Historical and real-time project data | Encoded objective functions, constraints, classical preprocessing |
| Strength | Interpretability and established practice | Pattern detection and adaptive analytics | Potential exploration of specialized optimization spaces |
| Key limitation | Manual/static updates under rapid change | Data quality, drift, opacity, governance | Noise, encoding cost, hardware limits, uncertain advantage |
| Validation priority | Baseline accuracy and control discipline | Out-of-sample predictive and decision value | Fair comparison with strong classical solvers |

### 4.4 Discussion

Table 1 summarizes an evidence-oriented comparison of the three project-management approaches. The practical implication for project organizations is an incremental adoption path. First, improve data governance and strengthen conventional controls. Second, deploy AI where a measurable prediction or classification task exists and where human review can remain in the decision loop. Third, identify optimization bottlenecks whose structure is suitable for rigorous solver comparison. Only then should a quantum or quantum-inspired experiment be introduced. This sequence limits technological novelty from overshadowing problem definition and evidence quality.

The framework also supports responsible adoption. AI-generated recommendations may be sensitive to incomplete or unrepresentative data, and generative tools may produce plausible but incorrect content. Quantum outputs can be misinterpreted when probabilistic solutions or experimental demonstrations are translated into operational claims. Governance should therefore include model documentation, access controls, validation

criteria, escalation rules, and explicit accountability. Organizational readiness is as important as algorithmic sophistication.

For researchers, the central opportunity is to move from broad claims to reproducible task-level studies. Promising target problems include multi-project resource allocation, constrained scheduling, portfolio selection, routing, supplier assignment, and risk-response optimization. Each study should state the mathematical formulation, dataset, classical baseline, quantum encoding, hardware or simulator details, performance metric, uncertainty, and computational cost. This approach can reveal where hybrid quantum–classical methods genuinely add value and where classical techniques remain preferable.

## V. CONCLUSION

AI and quantum computing represent different but potentially complementary pathways for advancing project management. AI has an increasingly established role in prediction, information processing, and adaptive decision support. Quantum computing offers a research frontier for structured optimization problems, particularly through hybrid quantum–classical approaches such as QAOA-based workflows. The strongest near-term strategy is not to replace traditional project management but to layer new computational capabilities onto transparent governance and validated decision processes. The three megaproject cases demonstrate the importance of cost, schedule, resource, and systemic risk, yet they do not by themselves prove counterfactual quantum benefits. A credible QAI-PM research agenda must therefore prioritize reproducibility, fair classical benchmarks, realistic hardware assumptions, human oversight, and evidence-based claims. Under those conditions, AI and quantum methods can be evaluated as practical tools rather than technological promises.

However, this study is limited by its retrospective cases and its reliance on simulation for the proposed QAI-PM layer. Historical megaproject data were generated under management conditions that differ from present AI and quantum ecosystems. The absence of a deployed QAI project-management system means that causal claims about avoided overruns or shortened schedules cannot be supported by these cases alone. Moreover, results from simulated quantum circuits should not be equated with performance on noisy hardware. Future studies should use prospective or rolling-origin evaluations in which only information available at each historical decision point is exposed to the model. AI models should be assessed with calibration, error, robustness, and decision-value metrics. Quantum studies should report optimality gaps, feasibility, runtime, sampling requirements, noise sensitivity, and scaling behavior. Cross-disciplinary experiments involving project managers, optimization researchers, and quantum-computing specialists would improve both practical relevance and methodological rigor.

## REFERENCES


[1]. Alshaikhi, A., & Khayyat, M. (2021). An investigation into the impact of artificial intelligence on the future of project management. In 2021 International Conference of Women in Data Science at Taif University (WiDSTaif) (pp. 1–4). IEEE. https://doi.org/10.1109/WiDSTaif52235.2021.9430234

[2]. Aliyev, A. (2025). The AI and quantum era: Transforming project management practices. Journal of Future Artificial Intelligence and Technologies, 1(4), 348–370.

[3]. Barcaui, A., & Monat, A. (2023). Who is better in project planning? Generative artificial intelligence or project managers? Project Leadership and Society, 4, 100101. https://doi.org/10.1016/j.plas.2023.100101

[4]. Beverland, M. E., et al. (2022). Assessing requirements to scale to practical quantum advantage. arXiv. https://doi.org/10.48550/arXiv.2211.07629

[5]. Biolcheva, P. (2021). The place of artificial intelligence in the risk management process. SHS Web of Conferences, 120, 02013. https://doi.org/10.1051/shsconf/202112002013

[6]. Blekos, K., Brand, D., Ceschini, A., Chou, C.-H., Li, R.-H., Pandya, K., & Summer, A. (2024). A review on quantum approximate optimization algorithm and its variants. Physics Reports. https://doi.org/10.1016/j.physrep.2024.03.002

[7]. Callison, A., & Chancellor, N. (2022). Hybrid quantum-classical algorithms in the noisy intermediate-scale quantum era and beyond. Physical Review A, 106, 010101. https://doi.org/10.1103/PhysRevA.106.010101

[8]. Corazza, M., Garcia, R., Khan, F. S., La Torre, D., & Masri, H. (2024). Artificial intelligence and beyond for finance (Vol. 15). World Scientific. https://doi.org/10.1142/q0449

[9]. Dacre, N., & Kockum, F. (2022). Artificial intelligence in project management: A review of AI's usefulness and future considerations for the project profession. https://doi.org/10.61175/DOGX9829

[10]. Felicetti, A. M., Cimino, A., Mazzoleni, A., & Ammirato, S. (2024). Artificial intelligence and project management: An empirical investigation on the appropriation of generative chatbots by project managers. Journal of Innovation & Knowledge, 9(3), 100545. https://doi.org/10.1016/j.jik.2024.100545

[11]. Gujju, Y., Matsuo, A., & Raymond, R. (2023). Quantum machine learning on near-term quantum devices: Current state of supervised and unsupervised techniques for real-world applications. arXiv. https://doi.org/10.48550/arXiv.2307.00908

[12]. Hashfi, M. I., & Raharjo, T. (2023). Exploring the challenges and impacts of artificial intelligence implementation in project management: A systematic literature review. International Journal of Advanced Computer Science and Applications, 14(9). https://doi.org/10.14569/IJACSA.2023.0140940

[13]. How, M.-L., & Cheah, S.-M. (2024). Forging the future: Strategic approaches to quantum AI integration for industry transformation. AI, 5(1), 290–323. https://doi.org/10.3390/ai5010015

[14]. Kim, D., Kang, J., Kim, T. W., Pan, Y., & Park, J. H. (2021). The future of quantum information: Challenges and vision. Journal of Information Processing Systems, 17(1), 19–36. https://doi.org/10.3745/JIPS.01.0063

[15]. Quiroz, G., Titum, P., Lotshaw, P., Lougovski, P., Schultz, K., Dumitrescu, E., & Hen, I. (2025). Quantifying the impact of precision errors on quantum approximate optimization algorithms. Physical Review Research, 7, 023240. https://doi.org/10.1103/PhysRevResearch.7.023240
[16]. Salimimoghadam, S., Ghanbaripour, A. N., Tumpa, R. J., Rahimi, A. K., Golmoradi, M., Rashidian, S., & Skitmore, M. (2025). The rise of artificial intelligence in project management: A systematic literature review of current opportunities, enablers, and barriers. Buildings, 15(7), 1130. https://doi.org/10.3390/buildings15071130
[17]. Taboada, I., Daneshpajouh, A., Toledo, N., & de Vass, T. (2023). Artificial intelligence enabled project management: A systematic literature review. Applied Sciences, 13(8), 5014. https://doi.org/10.3390/app13085014
[18]. Vieira, J., Poças Martins, J., de Almeida, N. M., Patrício, H., & Morgado, J. (2023). Reshaping the digital twin construct with levels of digital twinning (LoDT). Applied System Innovation, 6(6), 114. https://doi.org/10.3390/asi6060114
[19]. Weidenfeller, J., Valor, L. C., Gacon, J., Tornow, C., Bello, L., Woerner, S., & Egger, D. J. (2022). Scaling of the quantum approximate optimization algorithm on superconducting qubit based hardware. Quantum, 6, 870. https://doi.org/10.22331/q-2022-12-07-870
[20]. Widdows, D., Kitto, K., & Cohen, T. (2021). Quantum mathematics in artificial intelligence. Journal of Artificial Intelligence Research, 72, 1307–1341. https://doi.org/10.1613/jair.1.12702
[21]. Winker, T., et al. (2023). Quantum machine learning: Foundation, new techniques, and opportunities for database research. In Companion of the 2023 International Conference on Management of Data (pp. 45–52). ACM.
[22]. Vogel, M. (2011) "Quantum Computation and Quantum Information, by M.A. Nielsen and I.L. Chuang," Contemp. Phys., vol. 52, no. 6, pp. 604–605, Nov. 2011
[23]. Global Infrastructure Hub. (2025). The Channel Tunnel (United Kingdom–France) [Case study]. Ramboll.
[24]. Anbari, F. T., Giammalvo, P., Jaffe, P., Letavec, C., & Merchant, R. (2008). The Chunnel project. Project Management Institute.
[25]. Sydney Opera House: For demonstrating architecture's power to refine a city (Most Influential Projects: #50). (2019). PM Network, 33, 94–95. Project Management Institute.