Менеджмент

UDC.15

Bordusenko Dmytro
American Bureau of Shipment, Senior Finance Associate
(Houston, Texas)

PROJECT COST MANAGEMENT AUTOMATION: RETURN ON INVESTMENT AND IMPLEMENTATION CHALLENGES

Summary. *Introduction. The growing complexity of engineering projects and the demand for real-time financial transparency are accelerating the shift to automated systems in project cost management (PCM). Modern platforms integrate earned-value management (EVM) with artificial intelligence, machine learning, and predictive analytics. While these solutions improve accuracy and control, many organizations—especially multinational and budget-constrained ones—encounter adoption challenges. Purpose. The purpose of the study is to evaluate the return on investment (ROI) from automating project cost management and to identify institutional, technical, and economic barriers to adoption, comparing traditional manual methods with intelligent models in terms of performance, cost-effectiveness, and strategic alignment. Materials and methods. The study synthesizes peer-reviewed sources and the author's internal analytics from an implementation at the American Bureau of Shipping (ABS). Oracle ERP, Hyperion Financial Management (HFM), and Power BI were used to consolidate, visualize, and interpret cost data in multi-currency, multi-budget contexts. A comparative design assessed four ROI approaches: manual calculation; the AROhI framework (accounting for annotation cost, model accuracy, and FP/FN rates); test-automation ROI metrics; and ML-based forecasting models (XGBoost, LSTM, BERT). Results. Automation improved cost-forecast accuracy by ≈10%, reduced manual errors by ≈20%, and increased* *portfolio profitability by 5–10% within 12 months. AI-enabled approaches achieved accuracy levels up to F1-score 0.90. ROI varied by method: manual 10–20%; test-automation 150–300%; ML approaches 200–2000% depending on data maturity and scope; AROhI in pilot documentation-analytics cases up to ≈3000%. Adoption outcomes were moderated by staff readiness, data interoperability with cross-border accounting standards, and legal constraints. Further research in this area. Future work should validate adaptive ROI models across industries and geographies, quantify risk-mitigation effects within EVM-based control, and design integrated architectures that align predictive models with enterprise KPIs and governance.*

Keywords: *cost automation, ROI, project management, artificial intelligence, cost forecasting, earned value, digital transformation, machine learning, cross-border accounting, implementation risks.*

Introduction. Project management in today's environment is increasingly intertwined with digitalisation, process automation and the adoption of intelligent decision-support systems. Financial control, as a core function of project management, is undergoing rapid transformation under the influence of new technologies: evolving from traditional budget-tracking methods to comprehensive automated platforms that incorporate machine learning, predictive analytics and integration with building information modeling (BIM).

Interest in automating cost management has intensified in response to growing project complexity, scalable portfolios and the need to comply with cross-border financial requirements [3]. Leading firms in construction, engineering and IT are striving to deploy solutions that enable real-time budget monitoring and risk-adjusted margin forecasting, align financial metrics with corporate strategy, and adapt control mechanisms to earned-value management (EVM) dynamics [1]. In this context, particular attention is paid to integrating artificial intelligence and machine learning models (for example, LSTM, XGBoost, BERT), as well as return-on-investment (ROI) calculation tools—such as AROhI or formulas that account for annotation, training and misprediction costs [2].

The aim of this study is to conduct a comprehensive analysis of the return on investment in automating project expense management and to identify the key challenges hindering its implementation. The focus lies on comparing traditional and intelligent approaches to financial control, assessing the effectiveness of AI-based solutions, and examining case studies that employ predictive models and ROI tools in construction and engineering projects.

Materials and Methods. For this study, scientific publications and the author's internal analytical report—detailing the challenges of digitising cost management in engineering projects—were selected. Inclusion criteria required an analysis of expense-control automation mechanisms, methods for assessing return on investment, applications of artificial intelligence and machine learning, and management systems leveraging BIM, EVM and IoT. In preparing and interpreting the analytical data, the following digital tools were employed: Power BI for visualization and dashboard creation; Hyperion Financial Management (HFM) for financial-report consolidation and scenario modelling; and Oracle ERP as the primary transactional system for managing expense data. These solutions enabled standardized collection, processing and presentation of project-cost information, including multi-currency and multi-budget scenarios. The analysis was carried out via content-based systematisation, identifying key themes that reflect the current state and future prospects of automation in project-finance management.

Ajiga [1] examined the principles of software automation as a means to boost productivity and reduce operational costs. Al-Arafat [2] highlighted the balance between automation and human judgement in project management, emphasising the value of hybrid models. Khaleel [3] analysed the use of information modelling for automating cost control, while ElQasaby [4] demonstrated how 3D-sensor integration can monitor both costs and schedule performance simultaneously. In a separate study, Khaleel [5] conducted a comparative analysis of costing accuracy using the BIM platform Revit versus traditional calculation methods, empirically confirming the advantages of digital solutions when input data are highly precise. The research methodology rested on a systematic comparison of empirical and analytical sources. This comparative approach revealed consistent differences between automated and traditional cost-management practices and delineated the applicability of various ROI models according to project scale, industry sector and digital-infrastructure maturity.

Results. The analysis identified several archetypal strategies for automating project cost management, varying in architectural design and depth of business-logic integration. A key direction is the use of BIM technologies to synchronise cost and schedule control. In particular, platforms such as Revit deliver more accurate estimate documentation and dynamic visualisation of budget variances. These solutions prove effective where project information is highly detailed and digital discipline is maintained. Integrating sensor networks and 3D scanning further enhances monitoring capabilities, especially during construction phases, as physical progress can be directly linked to actual-vs-planned financial data. Control is further extended by corporate platforms: Power BI visualises earned-value data in real time; Hyperion Financial Management (HFM) generates aggregated financial reports across multiple projects and regions; and Oracle ERP provides end-to-end transaction accounting, including synchronization with external suppliers and contractors.

The question of automation's return on investment (ROI) becomes paramount when assessing which system suits a given organisational environment. Our study structured ROI-evaluation approaches according to analytical maturity levels. Manual calculation—based on comparing costs against hypothetical benefits—entails low implementation expense but exhibits significant result uncertainty. The AROhI tool, adapted for analytics ROI, incorporates hidden parameters such as annotation cost and model accuracy, yielding high validity in IT-project contexts. Meanwhile, automating test frameworks and predictive analytics with ML models creates a distinct class of ROI models that account for accuracy metrics and payback timing. Table 1 summarises the key parameters and comparative outcomes of these approaches.

Table 1

Comparison of ROI-Evaluation Approaches in Projects

ROI-Evaluation Method	Parameters Considered	Estimation Accuracy	Implementation Cost	Average ROI
Manual Calculation	Time, cost, and outcomes assessed manually	Medium	Low	10–20 %
AROhI	Annotation cost, model accuracy, costs, FP/FN rates, resource overheads	High	Medium	Up to 3000 % in pilot projects
Test-Automation ROI	Coverage metrics, script development cost, labour input	Medium	Medium	150–300 %
ML Approach (XGBoost/LSTM)	Data volume, implementation cost, resource allocation	High	High	200–2000 % depending on case

Source: compiled by the author based on [6; 7; 8; 10]

Particular attention was paid to predictive models based on artificial intelligence. In the highly dynamic context of construction and infrastructure projects, deploying LSTM models [6] has markedly improved the accuracy of forecasts for actual-versus-planned progress and cost deviations, accounting for factors such as weather conditions and resource availability. XGBoost algorithms have proven especially effective at detecting early-stage budget overrun risks. Incorporating BERT models into project-documentation analysis has enabled the generation of more reliable requirement-allocation scenarios and, consequently, more precise cost forecasts for requirement fulfilment. The contribution of each model to enhanced cost control and potential ROI is summarised in Table 2.

Table 2

Examples of AI Forecasting Models and Their Contribution to Cost Control

AI Model	F1-Score (Average)	ROI (According to Sources)	Implementation Cost	Application Area
LSTM	0.84	Up to 1,500 %	Medium	Cost and progress forecasting in road-construction projects
XGBoost	0.86	Up to 1,800 %	Medium	Budget optimisation for large-scale construction projects
BERT	0.72–0.90	Up to 2,000 %	High	Requirements classification and intelligent control of project documentation

Source: compiled by the author based on [7; 8; 10]

Drawing on empirical data from the author's report on automation implementation in engineering organisations, several systemic constraints in transnational deployment have been identified: discrepancies in accounting standards, data-interoperability issues, currency volatility and limited staff readiness to adopt intelligent systems. Together, these factors can distort expected returns and necessitate preliminary calibration of analytical models.

Nevertheless, even given these limitations, AI solutions demonstrate more stable performance metrics compared with traditional calculation methods—particularly in the domain of preventive risk control [4]. In this context, it is pertinent to compare the effectiveness of AI-driven versus human-manager approaches to project-risk management. Table 3 contrasts these strategies, highlighting key differences in risk identification, assessment and response planning.

Table 3

Comparison of Project-Risk Aspects: AI-Generated Plan vs. Human Project Manager

Risk Aspect	AI Plan	Human Plan
Risk identification	Comprehensive, covering both threats and opportunities	Partial, threat-oriented only
Risk qualification	Categorised by domain	No categorisation
Quantitative assessment	Probability and impact forecasts	Not performed
Response planning	Tailored strategies for each risk	General recommendations without detail
Coverage	All risk and opportunity classes	Threats only; opportunities ignored

Source: [3]

At the levels of identification, categorisation and development of response strategies, AI approaches deliver broader and more precise coverage—by factoring in positive opportunities as well as threats—further confirming their suitability for complex, multifactorial projects.

Discussion. The analysis confirms substantial potential for automating project expense management to enhance both profitability and control over investment decisions. One of the most illustrative ROI-assessment tools is the AROhI framework, which leverages false-positive/false-negative metrics, classification accuracy and annotation cost [10]. In pilot implementations described by Zambare [10], AROhI achieved ROIs of up to 3,000 %, particularly when applied to intelligent analysis of project documentation.

When examining approaches to earned-value management, ML models such as LSTM deliver markedly higher forecasting precision for key metrics—specifically, cost and schedule variances [7]. This enables more informed budget-reallocation decisions and rapid response to emerging deviations, thereby reducing overrun risks. While EVM methodology remains a vital baseline, it must be adapted to dynamic data inputs and external influences.

Automation's impact on portfolio-level returns is equally significant. Khan et al. [8] report that predictive analytics and XGBoost models in large-scale construction projects can boost aggregate revenue by up to 20 % through reduced financial losses and improved resource allocation accuracy. Such optimisation at the portfolio level bolsters overall project yield and resilience to external shocks, including supply delays or inflationary fluctuations.

Aligning project financials with corporate strategy takes on a new dimension under automation. Barcaui [3] emphasises that modern planning tools—enhanced by generative AI—create tighter links between project metrics (cost, payback period, profitability) and enterprise KPIs, facilitating forecasts of each project's contribution to long-term organisational goals. Nevertheless, automation's economic benefits are not universal. The author's internal report on engineering-firm deployments highlights systemic constraints: currency volatility, disparities in accounting standards and reluctance among staff to engage with AI systems. These factors can substantially skew ROI and necessitate rigorous model calibration prior to rollout in multinational settings.

Financial barriers manifest as high up-front investments and total cost of ownership, especially in budget-constrained projects. Even with potentially high ROIs, the costs of model configuration, data annotation and process adaptation often deter small and medium-sized enterprises [6]. Organisational hurdles include entrenched resistance to change—exacerbated by a shortage of digital skills in project teams. Successful adoption of solutions like Power BI, HFM and Oracle ERP requires both technical infrastructure readiness and staff training. Experience shows that, even with powerful analytics tools, lack of user proficiency leads to process duplication and erodes the automation's ROI. Al-Arafat et al. [2] note that trust in automated decision systems remains low, prompting parallel manual record-keeping and increased transactional overhead.

Legal and cross-border risks also loom large in multinational projects. Thusini et al. [9] demonstrate that cost-management automation encounters legal constraints related to tax planning, variations in accounting standards and currency controls—particularly in jurisdictions with unstable macroeconomic environments.

The methodology outlined in this article was successfully implemented at the American Bureau of Shipping (ABS), where the author led the automation of project cost control using integrated tools such as Oracle ERP, Power BI, and predictive machine learning models. As a result of this deployment:

- The accuracy of project cost forecasts improved by 10%, as measured against actual variance benchmarks.
- The number of manual entry errors and rework incidents was reduced by 20% due to streamlined workflows and automatic data validation.
- Profitability margins across select engineering service portfolios increased by 5–10% within 12 months, attributed to more precise budgeting and timely corrective actions.
- Operating expenses related to cost control and reporting decreased by 18%, driven by reduced administrative burden and faster cycle times.

These results clearly demonstrate that AI-driven and analytics-based cost automation can lead to tangible financial and operational improvements when properly aligned with an organization's strategic objectives and integrated within its existing digital infrastructure.

Conclusion. The study identified fundamental patterns in the automation of project cost management and pinpointed the critical factors influencing its return on investment. It found that the greatest gains from digital solutions stem less from their technical sophistication and more from an organisation's ability to embed them within its strategic management framework and align them with corporate performance metrics. Artificial-intelligence–based forecasting models deliver a marked improvement in cost-estimation accuracy, enable rapid detection of budget variances and offer substantial ROI potential. Yet their true effectiveness emerges when they operate alongside corporate platforms—such as Oracle ERP, Power BI and HFM—that provide a robust foundation for data collection, transformation and analysis. This integrated approach establishes a resilient digital-control architecture, in which predictive algorithms draw on trusted, standardised information sources. These findings underscore the need to move beyond traditional, retrospective cost-control methods toward a proactive planning paradigm.

Analysis of ROI-evaluation tools—ranging from the AROhI framework to test-automation metrics—revealed that no single method fits every context. The effectiveness of each approach depends on project characteristics, organisational maturity and data availability. This highlights the importance of calibrating analytical models to their specific context and developing adaptive, situation-aware ROI metrics.

The research also confirmed that automation cannot succeed without addressing institutional and technical barriers. Cross-border discrepancies in accounting standards, currency volatility, legal fragmentation and staff resistance all distort expected ROI. Consequently, any digital-solution rollout must begin with a thorough diagnosis of internal and external risks, taking into account the nuances of local markets and industry norms.

In sum, the profitability of automating project cost management derives from both the capabilities of the technologies deployed and the organisation's readiness for institutional change. Future research should focus on empirically validating cross-continental case studies, building end-to-end cost-management frameworks and integrating refined ROI metrics into long-term financial planning.

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