Technium Business and Management (TBM)
Vol. 12, pp.292-310 (2025)
ISSN: 2821-4366
www.techniumscience.com

AI-Powered Budgeting and Cost Estimation: Predicting Project Costs and Preventing Overruns

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Abstract

Artificial intelligence (AI) is reshaping project cost management and budgeting throughout the entire project lifecycle, from strategic planning and execution to monitoring, control, and closeout. Traditional methods reliant on periodic reporting and static forecasts have failed to keep pace with dynamic changes in labor, supply chains, and material costs, creating inherent cost and schedule risks across industries. Modern platforms now integrate predictive analytics, generative assistants, and natural language processing (NLP) to surface early risk signals and recommend resource allocation. Recent platform releases demonstrate this shift: Asana AI has introduced capacity-aware planning; ClickUp Brain leverages organizational knowledge graphs to quantify time savings; Notion AI automates multilingual meeting capture and synthesis; and SAP Analytics Cloud unifies real-time planning with predictive forecasting. Furthermore, British Airways' use of AI in its Mission Control and Pathfinder systems has demonstrated improved punctuality and decision quality at an operational scale. Vendor-reported results and case studies indicate significant reductions in manual effort, blind spots, variance detection time, and governance shortcomings compared to conventional approaches. This paper synthesizes emerging practices, compares AI-enhanced and conventional methodologies, and identifies pathways to avoid cost overruns and strengthen portfolio resilience.

Keywords
Artificial Intelligence; Budgeting; Cost Estimation; Pre-FEED / FEED; Project Management; Predictive Analytics; Raw Material Price Monitoring; Governance; Closeout; Forecasting; Capacity Planning; Real-time Monitoring

Introduction

Monitoring and controlling budget accuracy and schedule reliability are keys to successful complex project delivery, and yet ongoing variances from planned baselines continue to plague organizations across industries. While project management methodologies have evolved over the years, we still find that programmers are plagued with problems of cost and schedule overrun, which are often further aggravated by macro-economic turbulence, supply chain disruption and the complex interdependencies that characterize very large projects. The scale of this challenge is borne out by recent studies. A recent KPMG Construction Survey found C-suite executives in the engineering and construction sector continue to face the twin pressures of cost and schedule performance and the disconnect between strategy and actual performance of operational execution (KPMG, 2023). In the framework of the AI-driven Front-End Engineering Design (Pre-FEED/FEED) and cost management of the project, it is essential to incorporate the Market volatility, cross-project learning, and real-time execution indicators to enhance the precision of the forecasts and the quality of decisions. The volatility in the market, especially in commodities and foreign currency, directly affects sanction-grade estimates as well as the plan to use capital expenditure and this is why it is vital to monitor this continuously. With cross-project learning, organizations can take advantage of the experience of former Pre-FED/ FEED packages and improve benchmarking and refine probabilistic cost models. Indications of real-time performance, like productivity deviations, procurement delays, or schedule slippages, are used to feed AI to incorporate early warning, reduce decision latency, and make proactive interventions. According to the Pulse of the Profession 2024 by the Project Management Institute, these practices are urgently needed, and they state that a lack of a clear performance gap remains and that projects that had not developed a data-driven approach are much more likely to fail to meet their targets on time, scope, and cost. The implementation of AI-based, data-centric practices into FEED can not only enhance resilience and flexibility but also guarantee a more solid route to the delivery of predictable results in highly unpredictable market contexts.

Traditional estimation approaches have long been at the foundation of project planning activities. Expert judgment, analogous estimation, parametric models, and bottom-up cost decompositions offer structured approaches to forecasting budgets and timelines. Nonetheless, when implemented in practice, these approaches often take static forms and require significant resources, involving significant manual intervention and iterative changes. Moreover, they suffer from the inability to absorb variable market conditions or incorporate knowledge transferred at the portfolios' level in real time, causing a lag between the realization of nascent risks and managerial intervention (Fleming & Koppelman, 2016). Widespread is the use of cost control based on spreadsheet technology; it has the role of being mostly a retrospective monitoring tool rather than predictive, consequently leaving the organization at the mercy of cumulative variances.

One particularly powerful way to improve traditional practice is through adaptive, data-driven functionality that enhances forecasting and response using artificial intelligence (AI). Machine-learning models trained on both historical project data and real-time operating data can capture non-linear relationships and trends that are hard for human estimators to capture and can help to reduce cost and schedule overruns (Zhang et al., 2022). This is being further enhanced by applications of NLP (Natural language processing) and large language models to help translate unstructured documents-heavy engineering designs, supplier contracts, progress reporting-into actionable knowledge for more accurate estimates (Dwivedi et al. 2021). Besides the descriptive analytics and diagnostic analysis, the prescriptive AI model can also predict the probable intervention and suggest the most cost-effective resource or remedy allocation before general deviations (Margherita & Braccini, 2022).

This paper examines the integration of AI-based budgeting and cost estimating throughout the end-to-end lifecycle of international projects. It assesses both the theory and practice of AI-informed incorporation with respect to the timing of incorporation (e.g. project planning, execution, monitoring and control, and project closure). Analysis is supported by recent examples from enterprise platforms including SAP Analytics Cloud, Microsoft Copilot, Procore AI, and Asana Intelligence and real-world use case examples including Mission Control in British Airways. Together these cases illustrate how cost management is being transformed from a static, backward-looking, activity to a dynamic, predictive, and prescriptive practice with real benefits for project resilience and stakeholder value.

Background: Traditional Estimating and Control Vs. Continuous AI Governance

Conventional FEED and budgeting workflows typically apply fixed escalation factors updated quarterly or annually, with cost baselines validated at stage-gates. These methods offer traceability but suffer latency and limited adaptability. AI-enhanced governance operates continuously: it ingests structured enterprise data (ERP, budget, schedules), unstructured signals (RFIs, contracts, site notes), and external feeds such as commodity price indices and vendor quotes. The result is a rolling, probabilistic view of Estimate at Completion (EAC) and risk exposure that updates as conditions change.

Methods & Data: Signals, Features and Model Classes

Signals fall into four classes: (i) financial (budgets, commitments, actuals), (ii) schedule & progress (earned value, percent complete, critical-path shifts), (iii) operations & quality (RFIs, change logs, punch lists, safety), and (iv) market intelligence (raw-material prices, FX, logistics). Features include rolling lags, growth rates, seasonality, vendor-specific effects, weather-adjusted calendars, and cost code mappings. Models combine time-series forecasting for price trends, supervised learning for EAC prediction, anomaly detection for variance signals, and retrieval-augmented LLMs for narrative synthesis and root-cause drafts.

Continuous raw-material price capture is pivotal in FEED. Daily ingestion of indices (e.g., ethane, steel, copper) and vendor quotes enable probabilistic trend forecasts that directly update material take-off cost curves. Compared with static escalation, this reduces uncertainty bands and improves the realism of sanction-grade estimates.

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Rolling forecast update rule:

Let the forecast of the horizon cost **(HC)** at time **t** for horizon **t+h** be denoted by

$$\widehat{HC}_{t+h}^{(t)} = \alpha \widehat{HC}_{t+h}^{(t-1)} + (1-\alpha) f_\theta(X_t),\ \ \alpha \in [0,1] \qquad \widehat{HC}_{t+h}^{(t)}$$

The rolling update combines the prior forecast with the latest model-based estimate as

$$\alpha \widehat{HC}_{t+h}^{(t-1)}$$

Where: — previous forecast for the same horizon (issued at time t−1).

$f\theta$ (X_t) — model output based on the current features X_t (e.g., progress, RFIs, procurement, and market indices).

α — smoothing weight balancing inertia and responsiveness.

Higher alpha = more weight on old forecast; lower alpha = more weight on new model output.

Early-warning threshold Rule (cost Risk):

Let $P(EAC^{(t)}$ denote the predictive distribution of the Estimate at Completion (EAC) at time t. A cost-risk alert is triggered when the probability of exceeding the Budget at Completion (BAC) plus an overrun allowance Δ exceeds a governance threshold:

$$P(EAC^{(t)} > BAC + \Delta) = 1 - F_{EAC}^{(t)}(BAC + \Delta) \geq \tau_c$$

In practice, it is tuned to organizational risk tolerance, and alerts trigger predefine prescriptive playbooks subject to management approval when the likelihood of overrun becomes significant.

AI in Global Project Planning

Strategic planning transforms objectives into a costed and resourced delivery plan. In conventional practice, planners rely on historical analogies, top-down targets, and fragmented capacity views, which can obscure bottlenecks and create optimism bias. Asana AI's recent releases introduce capacity planning and effort recommendations by learning from past throughput and upcoming demand, enabling managers to balance portfolios and set realistic baselines that reflect true constraints (Asana, 2025; Asana Help, n.d.). ClickUp Brain connects

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projects, documents, and people to form a unified knowledge graph that surfaces implied dependencies and risk hot spots, while the vendor reports faster task completion and time savings that translate into lower indirect costs (ClickUp, n.d., 2024). In capital projects, Procore's financials and analytics support forward-looking budget snapshots and forecasting entries that evolve as scope details mature, improving sensitivity analysis for owner and contractor contingencies (Procore, 2025a; Procore, 2025b). SAP Analytics Cloud integrates planning with predictive analysis so planners can simulate scenarios, generate plans from predictions, and move from insight to action without leaving a single environment (SAP, 2025a; SAP, 2025b). These capabilities reduce planning rework, align capacity with scope, and create traceable rationales for estimate assumptions. Compared with static baselines, AI-enhanced planning improves estimate realism, narrows confidence intervals, and shortens the time from concept to approved budget.

AI in Planning: Capacity-Aware Baselines and Market-Linked Estimates

In the PRE-FEED and FEED stages it is important to incorporate continuous monitoring of market price in the planning to generate commercially viable estimates. Historical throughput data and future demand may be used by artificial intelligence to set capacity-sensitive baselines, and real-time surveillance of the commodity and energy markets can be used to keep cost estimates up to date with the real situation. As an example, unpredictability in international steel costs, or LNG freight prices throughout FEED, can have a significant impact on capital expenditure projections, and dynamic pricing inputs are essential. By combining such information with portfolio-level what-if simulations, organizations can compare the strategies of procurement, including early purchase, staged contracting or hedging with different price regimes and varying foreign exchange conditions. The integration of that type of approach into the project design in its early stages will promote the agility of procurement, reduce the risk of cost overruns, and improve the commercial robustness of FEED deliverables (Shafaay et al., 2025; Maleky Khorram and Hamidian, 2023).

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Vol. 12, pp.292-310 (2025)
ISSN: 2821-4366
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Illustrative FEED market-price monitoring:

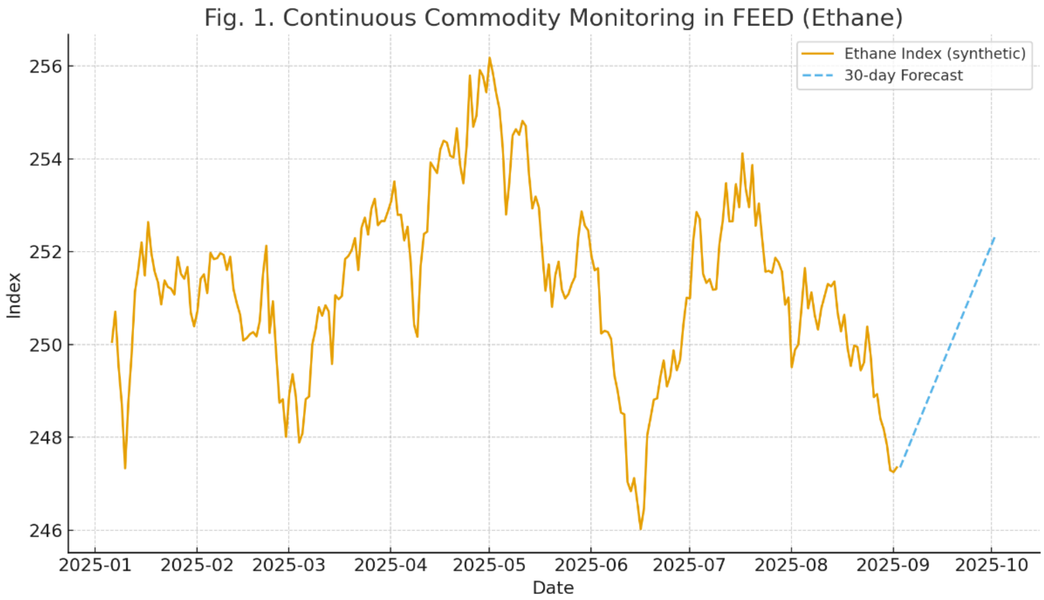

Figure 1. Synthetic ethane price series with naïve 30-day forecast (for illustration only).

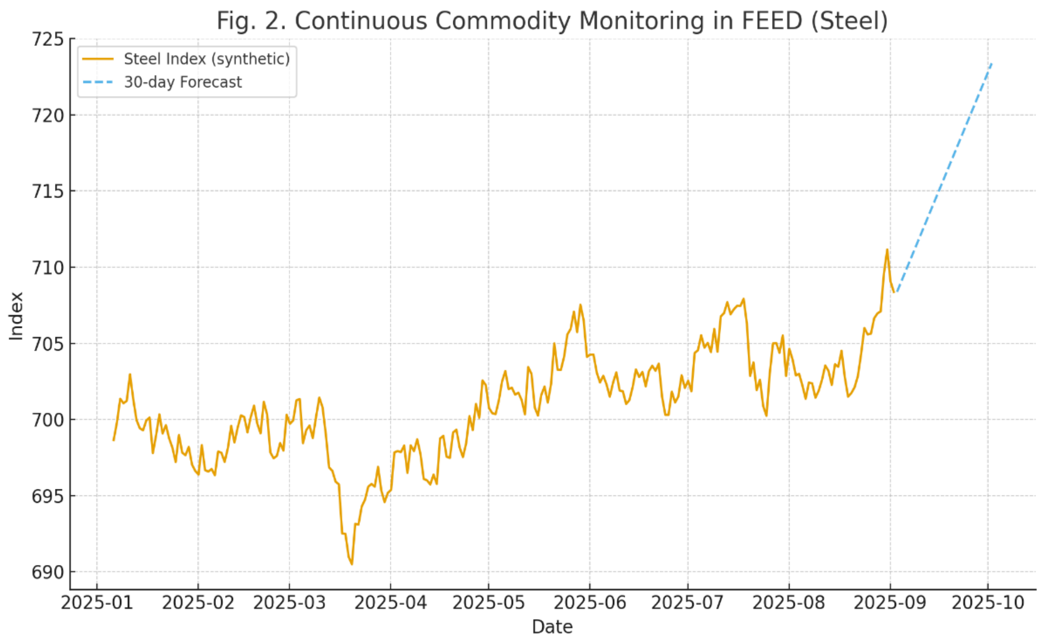

Figure 2. Synthetic steel price series with naïve 30-day forecast (for illustration only).

AI in Global Project Execution

Success of execution depends on clear information flow, timely decisions, and disciplined change control. Teams using Notion AI can capture meetings with automated transcription and obtain structured action summaries and follow-ups inside the same workspace, including translation where needed, which limits miscommunication across regions and accelerates alignment on scope and costs (Notion, 2025; Notion Meeting Notes, 2025). Microsoft's Copilot for Project Operations and Microsoft 365 provide generative task-plan suggestions with durations and effort, rapid report generation, and conversational insights over enterprise work data, shortening the cycle time to replan when issues arise (Microsoft, 2024; Microsoft, 2025a; Microsoft, 2025b). Atlassian's AI features in Jira and Jira Service Management streamline backlog grooming, suggest field values, and speed issue resolution, improving flow efficiency and reducing expensive idle time on critical paths (Atlassian, 2024, 2025). Monday.com's AI-first products introduce portfolio risk detection and automated summarization that keep stakeholders synchronized, helping prevent downstream cost growth caused by late discovery of scope or dependency conflicts (monday.com, 2025a, 2025b). These execution supports converting scattered updates into coherent, real-time narratives of progress and risk, enabling prompt corrective actions that
contain cost exposure.

AI in Execution: Faster Replanning and Coordination

At the stages of execution, AI copilots not only summarize the meetings, write action items, and ensure that the updates of various tools have been reconciled; they are also at the center of quicker replanning and improved coordination. Anomaly detection modules are constantly on watch of schedule slippage, material delays and exposure of cost. Commodity trends that put budgets at risk like a spike in the price of steel or cement prices can be detected early enough by the procurement and construction planner, and interventions like resequencing tasks, negotiating repricing terms or finding alternative sources can be undertaken. The Marcasa development project in Dubai was an example of a practical application that incorporated an AI-driven construction management system and was able to cut the turnaround time of engineering submittal by 57 percent, enhance the accuracy of reporting and anticipate risk solutions through sentiment analysis and automated risk scoring. That enabled the project management team to replan parts of the schedule dynamically as the supplier lead times increased, without having to propagate delay. These mechanisms help make sure that execution is dynamic, reduces cost overflow and facilitates cross-disciplinary coordination of engineering, procurement, and on-site operations. (Tahboub, 2024)

AI in Global Project Monitoring and Control

Project governance refers to that subset of the measurement and control activities related to identifying and controlling deviations from the cost, schedule, and scope baselines. Very similar methods to EVM, the frequency-based status reporting method, and the human in loop variance review method are still widely used for compliance and formal reporting purposes (Fleming & Koppelman, 2016). They are latency-poor solutions: project teams are likely to discover performance weaknesses at the end of periodic intervals and have little or no time to proactively address them. All these activities are being executed while continuously integrating forecasting, anomaly detection and predictive intervention using artificial intelligence (AI). As the article notes, ML can use AI to analyze structured enterprise resource planning (ERP) data and unstructured project signals to identify potential risk earlier and make recommendations for remediation before anything is lost in material overruns (Davenport & Mittal, 2022). This process is slowly becoming more efficient and moving from reactive control of the business via reports to real-time dynamic governance and enhanced decision making in industries around the world.

AI in Monitoring & Control: ERP Integration and Streaming Alerts

Embedding predictive planning within ERP unifies actuals with forecasts. Cost controllers view rolling EAC ranges, with alerts triggered by deviations in market-linked material curves, productivity, or vendor lead-time. Over-the-top dashboards provide evidence trails—each alert stores feature-level contributions and recommended actions.

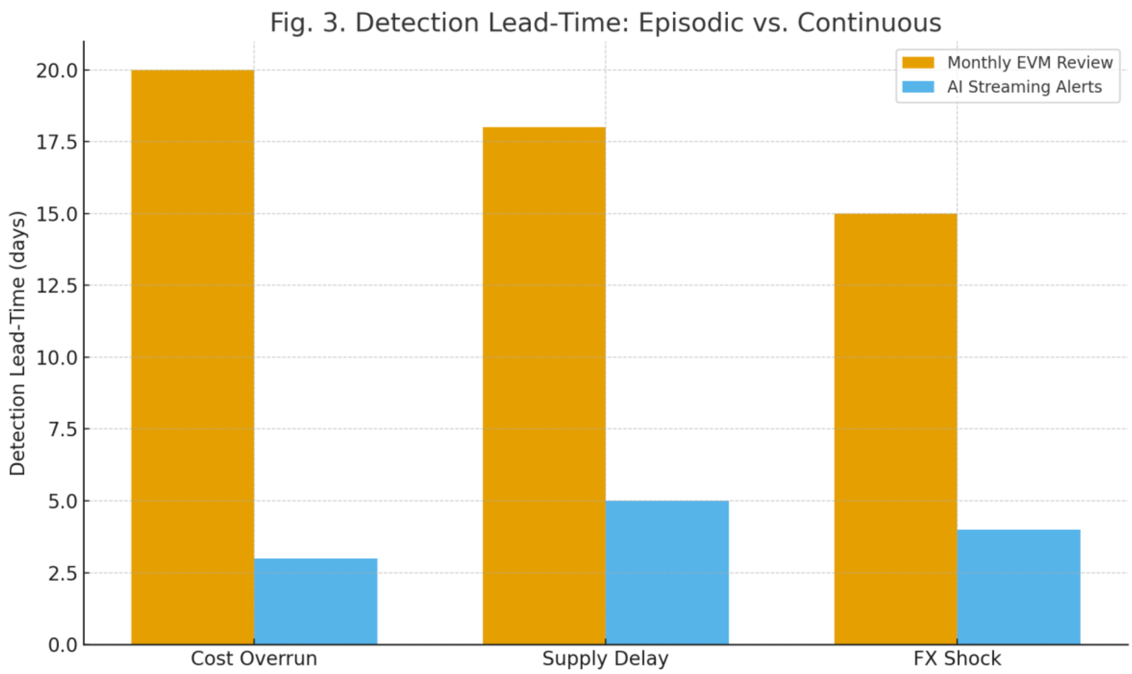

Figure 3. Illustrative detection lead-times (synthetic). AI enables earlier warnings vs. monthly reviews.

Technium Business and Management (TBM)
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ISSN: 2821-4366
www.techniumscience.com

Enterprise Applications: From ERP to Predictive Planning

Enterprise platforms are at the forefront of embedding AI into monitoring and control workflows. SAP Analytics Cloud, for instance, integrates predictive planning models and embedded analytics that link directly with ERP data to provide real-time variance signals and cash-flow projections. This integration reduces blind spots that would otherwise delay decision-making, allowing project managers to detect cost pressures earlier and align procurement or resourcing strategies accordingly (SAP, 2025a; SAP, 2025b). Artificial intelligence in a nutshell allows enterprise resource planning (ERP) systems to transform into inert storage of transactional information into engines of foresight. Modern business solutions are even more likely to incorporate predictive planning, conversational summarization, and anomaly detection that transforms data about operations into insights. One of these recurring patterns is the native integration of the ERP actuals with forecasting services automatically creating plan suggestions, or AI assistants transforming unstructured data like meeting notes or emails into audit ready stories. Not only does this increase decision making, but also compliance and transparency due to less reliance on manual reporting. However, due to the rate of vendor adoption and potential of offered features marketing hyperbole, organizations are advised to independently authenticate asserted capabilities with objective key performance indicators (KPIs). The recent Fin Robot architecture (Yang et al., 2025) shows how generative AI agents as part of ERP operations can shorten processing time by up to 40 percent and radically decrease error rates accompanied by audit controls where a definite benchmark can be set to assess vendor claims.

Construction Sector: Proactive Risk Mitigation

The construction industry illustrates the operational value of AI-driven monitoring. Procore, a leading construction management platform, has introduced AI agents and analytics that scan Requests for Information (RFIs), safety observations, and external datasets such as weather forecasts. These systems flag high-risk cost items and predict schedule disruptions, enabling project control teams to re-sequence activities and adjust procurement strategies before risks crystallize (Procore, 2024; AInvest, 2025). Given the high sensitivity of construction projects to weather, labor availability, and supply chain volatility, AI tools improve both responsiveness and resilience. Since construction projects are sensitive to weather oscillations, logistics, and labor, and volatile commodities; AI agents with a combination of RFIs, safety observations, and market indices can forecast cost escalation in time to facilitate a remedial response. This minimizes risk, ensures contingency and enhances resilience of the project in general. It has been demonstrated in 2024 that Construction Cost Indices (CCIs) can be predicted significantly better with the help of AI / hybrid models, which allows project stakeholders to be more proactive in preparing at the prospect of cost changes. (Buildings, 2024)

Operations-Scale Example: British Airways

A compelling real-world case is provided by British Airways, which has publicly credited AI-enabled systems for its record on-time performance. Public sources note the airline's use of Mission Control and Pathfinder platforms, which combine real-time data with historical operational records to optimize routing, gate allocation, aircraft stands, and crew assignments (Financial Times, 2025; The Times, 2025; BA Media Centre, 2025). The airline's experience demonstrates how predictive monitoring and AI-informed decision-making translate into measurable operational outcomes, such as reduced delays, lower fuel costs, and enhanced customer satisfaction.

Operational platforms that combine real-time telemetry data with the past trend of operational records like unified mission-control stacks illustrate the role of predictive monitoring on the latency of decisions and operational performance. The experience of the airline explains how predictive monitoring and AI-based decision-making can turn into quantifiable advantages, such as less time wasted on delays, a decrease in fuel expenses, and improved customer satisfaction. Other applications to similar architectures are engineering, procurement, and construction (EPC) programs, whereby cohesive data streams will reduce handoffs, enhance transparency and act to cause earlier and auditable interventions that reduce risk and enforce delivery performance.

Considerable recent research on the topic of "Data-Driven Analysis of the Supply Chain Integration Effect on Procurement Performance in International EPC Projects" (Huang and Li, 2024) confirms this: it demonstrates that a higher degree to which the flows of information across supply chain, procurement, and contract management are interconnected is statistically correlated with statistically significant improvements in both the predictability of cost and schedule incidences.

Portfolio-Level Governance and Contingency Management

The principles demonstrated at operational and project levels extend naturally to enterprise-wide project portfolios. Centralized AI models can aggregate heterogeneous data streams—including financial, operational, and external signals—to forecast deviations across multiple programs. Compared to human-only review cycles, these models detect patterns of risk earlier and with greater accuracy, enabling executives to intervene with more disciplined contingency drawdowns and governance oversight (PwC, 2023).

This contributes not only to improved project performance but also to strategic alignment, as organizations can reallocate resources dynamically based on predictive signals of under- or over-performance. Centralized models aggregate heterogeneous streams—financial, schedule, procurement, and market-price indices—to forecast deviations across programs. Executives can commit contingency with stronger rationale, reallocate resources proactively, and enforce consistent decision logic via playbooks.

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ISSN: 2821-4366
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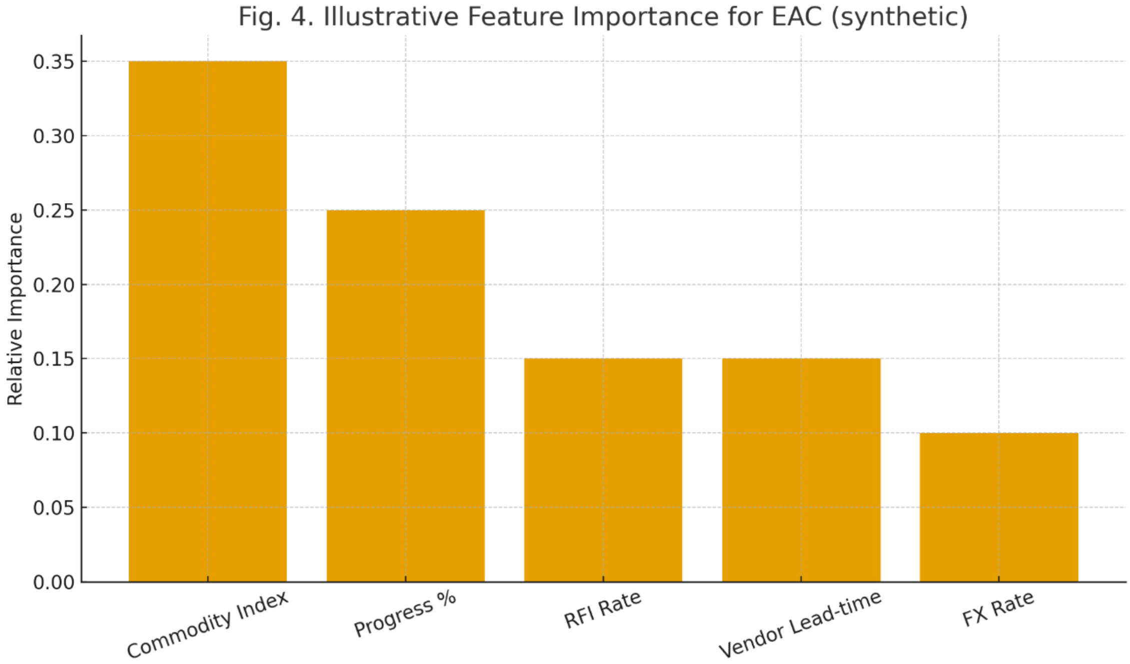

Figure 4. Synthetic model features indicate strong contribution from commodity indices.

Comparative Analysis: Effort, Latency, Accuracy, and Governance Quality

Traditional FEED estimates typically rely on static escalation factors and episodic human reviews. AI-enhanced approaches operate continuously and integrate market-price monitoring, lowering blind-spot risk and decision latency. In practice, teams target ±10% early-phase accuracy with disciplined data pipelines, versus ±25–30% when relying on fixed escalation and monthly re-estimates. Equally important, AI workflows preserve auditability by attaching explanations, sources, and decision rationale to each alert and replan.

BUSINESS & MANAGEMENT
Technium Business and Management (TBM)
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ISSN: 2821-4366
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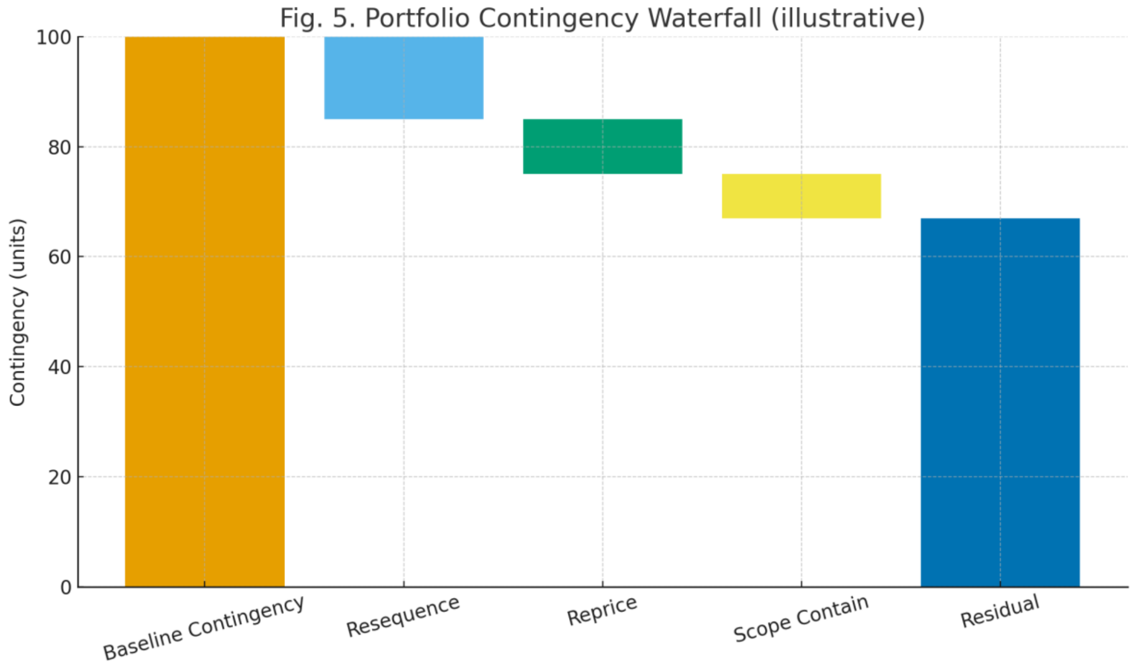

Figure 5. Illustrative contingency changes as AI-informed interventions reduce exposure (synthetic).

AI in Project Closeout

Closeout often suffers from knowledge loss and manual compilation of reports, diminishing the learning rate of organizations. Generative AI reduces this waste by synthesizing lessons learned, extracting causal patterns from decisions and change logs, and creating executive narratives tied to cost and schedule outcomes. Notion AI can convert large volumes of notes, tickets, and documents into a coherent closure report with inline citations to source pages, which streamline audits and accelerates knowledge transfer to successor initiatives (Notion, 2025). Tableau's AI-assisted analytics provide visual variance narratives that help finance and PMO teams identify recurrent drivers, closing the loop with planning standards and estimating guides (Tableau, 2025). When paired with enterprise assistants such as Copilot, organizations can institutionalize templates that automatically generate benefits realization summaries and contract closeout checklists, reducing administrative overhead while preserving institutional memory (Microsoft, 2025a).

Technium Business and Management (TBM)
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Comparative Analysis: AI-Enhanced vs. Traditional Methods

Implementation Playbook: Data Model, Governance, and Stage-Gates

A staged rollout reduces risk while building capability. Key elements include data operating model, market-data pipeline, model-risk management, decision rights, and change leadership. The tables below provide a practical checklist and KPIs.

Table 1. Traditional vs. AI-Enhanced FEED and Control

Dimension	Traditional Methods	AI-Enhanced Methods
Cadence	Reviews at fixed milestones (e.g., design freeze, quarterly cost updates)	Continuous progress monitoring with streaming data, exception alerts, and rolling reviews
Inputs	ERP actuals, cost reports, engineering drawings, static baselines	ERP + live IoT sensor data, RFIs, supplier lead times, raw-material indices, FX rates
Price Treatment	Uses fixed escalation factors (e.g., 3–5% inflation per year)	Dynamic commodity curves updated daily with forecasting models for steel, FX, and energy
Lead-time to Detection	Variances detected after reporting cycles (2–6 weeks delay)	Automated anomaly detection highlights deviations within hours or days
Early-phase Accuracy	Conceptual estimates ±25–30% at FEL-1/FEL-2	Predictive models target ±10% accuracy at FEL-1/FEL-2 through multi-source data fusion
Auditability	Relies on manual notes, spreadsheets, and report archives	End-to-end data lineage with system-logged decisions, alert-linked explanations
Governance	Decision rights unclear; risk managed reactively after overruns	Formal data governance council, proactive model-risk management with stress testing
Stage-Gates	Stage reviews tied to calendar milestones with lagging KPIs (cost variance, delays)	Adaptive stage-gates triggered by real-time KPIs (forecast accuracy, supplier risk index)

Change Leadership	Stakeholder resistance, limited communication, adoption driven by compliance	Continuous change leadership with dashboards, training, and structured feedback loops

Table 2. KPI Set and Definitions

KPI	Definition	Target / Usage
Forecast Accuracy (%)	Deviation between projected cost/schedule estimates and actual performance.	Target ±10% in early phases (FEL-1/FEL-2).
Variance Detection Time	Average time taken to identify deviations from project baselines.	Detect anomalies within hours/days (vs. weeks).
Data Integration Rate (%)	Percentage of relevant data sources connected to the central data pipeline.	Aim for >90% integration across core systems.
Audit Trail Coverage (%)	Proportion of system actions with traceable lineage and documented explanations.	Ensure 100% traceability for compliance.
Adoption Rate (%)	Percentage of stakeholders actively using AI dashboards and tools.	Target >80% adoption among key stakeholders.

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Table 3. Example Commodity Mapping for EC FEED (illustrative)

Commodity	Update Freq	Integration	Use in Cost Model	Weight (Example)
Steel (Plate/Rebar)	Daily / Weekly	Market indices + supplier feeds	Structural material cost driver	35%
Copper	Daily	LME index + procurement contracts	Electrical systems, cabling, and equipment	20%
Aluminum	Weekly	Exchange rates + supplier data	Piping, cladding, lightweight structures	10%
Cement	Monthly	Regional price bulletins + vendor quotes	Civil works and foundations	15%
Diesel/Energy	Weekly	Fuel price trackers + local suppliers	Equipment operation, logistics, power costs	10%
FX (USD/PKR)	Daily	Currency fees + central bank rates	Imported equipment/materials	10%

Traditional project cost estimation and control mechanisms have long relied on periodic human analysis, static baselines, and spreadsheets. While these methods offer a degree of transparency and historical traceability, they remain limited in responsiveness and adaptability. The reliance on static baselines means that deviations are only visible after they have already occurred, while lagging indicators provide too little lead time for corrective action. Similarly, the handoffs between disparate tools such as between financial software, scheduling applications, and reporting dashboards—often create brittle workflows that increase the probability of oversight or misinterpretation (KPMG, 2023). In an era of rising project complexity and compressed delivery schedules, such approaches are increasingly insufficient.

AI-enhanced approaches, by contrast, introduce continuity and adaptability into cost estimation and control. By operating continuously rather than episodically, AI systems can ingest both structured data, such as budgets and schedules, and unstructured data, such as emails, contracts, and field notes. Machine learning models then generate probabilistic forecasts that become more accurate as new information arrives. This creates a dynamic model of project performance that not only tracks current cost status but also predicts likely deviations before they materialize (ClickUp, n.d.; Microsoft, 2024). In practice, such systems enable rolling forecasts, automated variance analysis, and anomaly detection that drastically reduce blind spots in cost reporting.

Across the planning and execution continuum, the adoption of AI-driven cost control has been linked with shorter replanning cycles, earlier detection of risks, and measurable reductions in both effort and cycle time (Procore, 2024). For instance, Procore has incorporated AI in its construction management platform to predict probable cost overruns by interpreting Requests for Information (RFIs), subcontractor histories, and procurement records. This enables project managers to carry out forward-thinking measures, such as resequencing work or renegotiation of vendor deals, prior to cost increases being final. Furthermore, the integration of AI-powered analytics into Microsoft's project management solution enables organizations to automate the monitoring of budgets and provide greater visibility of capital spend to effectively improve accountability within portfolios (Microsoft, 2024).

Industry-wide research confirms the need for such a level of upgrading. KPMG's 2023 Global Construction Survey found that the majority of companies are experiencing repeated cost and schedule overruns, and nearly a third of companies report cost overruns of at least twenty percent above approved budgets. Results such as these demonstrate structural inefficiencies inherent in conventional cost management processes. By using integrated models that combine their calendars and purchasing information with their financial and operating numbers, firms addressing AI within the governance framework remove those inefficiencies.

Risks and Limitations

The implementation of AI-enhanced FEED and cost-control solutions is linked to several hazards and shortcomings that are to be clearly identified. One important issue is the model drift whereby predictive accuracy reduces as time goes by due to changes in input distributions or market dynamics. Indicatively, due to a sudden shift in the commodity prices, geopolitics disruptions or even unexpected supply-chains failure may make the models that seemed dependable unreliable. The quality of data is also an equally serious problem: incomplete purchase reports, discrepancies in ERP feeds, or unauthenticated third-party indices could create noise or systematic errors which will be transmitted by forecasts. The other limitation is due to bias in training data and model design. Representation of specific regions, commodities, or types of contracts may result in biased information, which lessens the capability of the system to generalize across a variety of projects. Organizations are also at risk of too much belief in vendor claims and black-box AI solutions, where there is not much transparency into model assumptions and methods and effective oversight is consequently limited. Even procurement indices can be susceptible to change in the methodology used by providers, and this can change comparability of the base across time. In the meantime, FX volatility and

Technium Business and Management (TBM)
Vol. 12, pp.292-310 (2025)
ISSN: 2821-4366
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logistics shocks can breach the statistical assumptions of stationarity and lead to material performances which leave material departures.

The mitigation solutions should be multi-layered. There should be institutionalization of model-risk management frameworks that are independent in nature as well as those that employ challenger models and drift-monitoring tools employed to give early warnings. Lineage and provenance controls are very necessary in assuring traceability of data sources thus enhancing auditability and compliance. Human in the loop approvals in high impact decisions like contract awards, large contingency draws, or long-term hedging commitments can be useful to keep accountability and prevent automation bias. Taken together, all of these address the efficiency benefit of AI-based systems and the governance protections needed to adopt AI responsibly.

Discussion

Enterprises need to define a data operating model across programmatic hierarchies, cost codes, resource characteristics, and document taxonomy to help AI models learn across programs without crossing privacy or contractual boundaries for cross-program learning, Human oversight will still be required: cost engineers, planners, and project managers must challenge recommendations, calibrate models to the local environment, and be alert for spurious correlations. Where AI is used to help make decisions in negotiations or to make claims in commercial transactions, for example, its use should be accompanied by ethical guardrails including transparency, explicability, and provenance of training data. From a capability standpoint, PMOs can implement AI-enabled estimating playbooks, and predictive dashboards directly into stage-gate decisions, and hard-code closeout synthesis as a deliverable. Real-world examples of the positive side of AI instrumentation combined with process rigor are provided: flight operations at scale, capital project forecasting, and enterprise work management platforms have all delivered measurable improvements in timeliness, coordination, and quality of decisions (BA Media Centre, 2025; Procore, 2024; SAP, 2025a).

Conclusion

Conclusion and Research Agenda

AI is transforming cost control into a continuous learning system that combines financial and execution signal, procurement and market-price-signal all in near real time, periodic, retrospective activity. The feature of dynamic adaptation decreases the latency in decision-making and increases the confidence in planning and performance by AI. The greatest advantages are seen in FEED, where the monitoring and forecasting of commodities reinforce sanction grade forecasts, and execution, where anomaly-based techniques can be used to speed up corrective actions and shrink decision-making. All these abilities bring organizations to a

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ISSN: 2821-4366
www.techniumscience.com

point where they are managing risks proactively as opposed to reactively to crisis management. In the future, there is need to have a systematic research agenda to develop both theory and practice. The standardization of benchmarks of AI-assisted cost forecasting takes one of the high priorities, as the benchmarks should be compared and be comparable across industries, regions, and procurement models. The second research question needs to be the generalizability of AI techniques to asset classes. No less significant is the necessity to test the action mechanisms: how do the warnings of early signs based on anomaly detection or monitoring of commodity drift, translate into quantifiable effects of cost containment and project outcomes improvement?

The barriers to organizational adoption (e.g. trust in AI output, compatibility with traditional governance structures and the automation/human control trade-off) should also be explored further under research. The longitudinal studies might evaluate the redesigning of the contracting strategies, contingency planning, and the capital allocation on the portfolio level by continuous feedback loops. Overall, although AI promises apparent opportunities to make FEED and execution more resilient and adaptive, researchers will also need to continue their research to optimize the process, test the findings, and implement governance principles to balance innovation and responsibility.

AI strengthens the accuracy and resilience of budgeting and cost estimation by transforming project data into timely guidance across planning, execution, monitoring, and closeout. Modern tools enable capacity-aware baselines, continuous forecasting, and automated documentation that together lower the probability and magnitude of overruns. The comparison with traditional methods indicates clear efficiency gains and risk reduction when AI augments established practices, provided organizations invest in data quality, change leadership, and responsible governance. As platforms evolve, the most significant value will come from cross-system integration that unifies financial, schedule, and operational signals, allowing leaders to anticipate rather than react to variance.

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Technium Business and Management (TBM)
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