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RESEARCH ARTICLE

INTEGRATED COST-SCHEDULE AND PROCUREMENT ANALYTICS FOR CONSTRUCTION SUPPLY CHAINS IN SAUDI MEGA-PROJECTS: ENHANCING FORECASTING AND PROJECT DELIVERY UNDER VISION 2030

Amaan Ullah Sharif Mohammed

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Abstract

Saudi mega-projects operate through dense networks of designers, contractors, manufacturers, logistics providers and specialist suppliers, so cost and schedule performance cannot be governed effectively as separate reporting streams. Procurement commitments shape the timing and price of resources; schedule changes alter purchasing priorities and logistics demand; and commercial variations feed back into forecast completion cost. This review develops an integrated framework for cost-schedule and procurement analytics in construction supply chains, with particular relevance to Saudi Arabia's Vision 2030 delivery environment. Thirty peer-reviewed studies published from 2020 to 2025 were synthesised across artificial intelligence in construction management, project cost prediction, schedule forecasting, construction supply-chain modelling, resilience and digital-twin-enabled control. The evidence indicates that predictive value emerges when cost, schedule and procurement records share consistent identifiers, timestamps and decision horizons. Machine-learning and hybrid models can improve forecasting, but isolated accuracy is insufficient unless outputs expose uncertainty, identify drivers and trigger accountable management action. Procurement analytics provides the operational bridge by converting predicted variance into package sequencing, supplier alternatives, expediting, inventory or contract responses. Digital twins and connected data environments further strengthen the feedback loop by linking planned and actual states. The proposed framework contains six layers: integrated project data, data alignment, predictive analytics, early-warning intelligence, procurement decision support, and delivery-outcome learning. Governance requirements include data quality, explainability, human review, model recalibration and procurement compliance. For Saudi mega-projects, the framework supports more reliable completion forecasting, earlier intervention and stronger supply-chain coordination while preserving professional judgement over commercial decisions.

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Corresponding Author:- Amaan Ullah Sharif Mohammed

Introduction:-

Saudi Arabia's Vision 2030 has created a construction environment characterised by large capital programmes, ambitious completion targets, extensive international sourcing and increasingly digital project controls. Mega-project delivery depends on thousands of linked decisions concerning scope, quantities, packages, suppliers, sequencing, logistics, payment and risk allocation. In such settings, cost, schedule and procurement are not independent management disciplines. They describe different dimensions of the same production system. A delay in a design release can postpone a tender; a late award can compress fabrication and transport; acceleration can increase commercial exposure; and supplier underperformance can simultaneously alter cash flow, critical-path logic and forecast final cost.

Research on artificial intelligence in construction increasingly recognises this interdependence. Reviews report strong applications in cost estimation, scheduling, risk prediction, monitoring and decision support, while also noting fragmented data, limited interoperability and the continuing need for human judgement [1-5]. Project-management research similarly suggests that artificial intelligence can enhance planning and predictive decision-making when algorithms are treated as decision aids rather than replacements for experienced managers [6-9]. The challenge is therefore not whether predictive technology can calculate a cost or duration estimate, but whether organisations can connect multiple project data streams into a coherent control process.

The cost dimension is especially important in Saudi mega-projects because uncertainty is introduced before construction begins and continues throughout execution. Studies of Saudi building projects identify contractual, managerial and delivery factors that contribute to cost and time overruns [16,17]. Early-stage modelling demonstrates that project cost and overall risk can be forecast from limited information, while machine-learning methods can capture nonlinear relationships that conventional estimating may overlook [18-20]. Yet a forecast created without schedule or procurement context is incomplete. A projected cost increase may be caused by delayed design, a supplier quotation, low productivity, a logistics constraint or a change in sequence. Each cause requires a different management response.

Schedule analytics has a parallel limitation when treated independently. Predicting completion dates or delay probability is valuable, but the schedule alone does not reveal whether a threatened activity can be recovered through an alternative supplier, earlier purchasing, different packaging or revised commercial terms. Hybrid deep-learning research indicates that construction duration estimation can incorporate spatial, temporal and uncertainty-related variables [8]. Digital project-management studies also show how integrated data can support real-time monitoring and corrective action [7,28,29]. The operational value of these techniques increases when schedule signals are linked to procurement status and commercial exposure.

Construction supply-chain research provides the third component. Systematic and quantitative reviews show that construction supply chains remain fragmented, project-based and vulnerable to unreliable information, capacity constraints, late materials and disruption [21,22]. Recent resilience studies demonstrate the value of back-up sourcing, inventory strategies, robust optimisation and digital visibility [23-26]. These findings imply that procurement should not be treated only as an administrative purchasing process. It is a control mechanism through which predicted cost and schedule risks can be mitigated.

This review develops an integrated analytics framework that connects these three disciplines. It focuses on how common data structures, predictive models, early-warning rules and procurement actions can improve forecast reliability and project delivery in Saudi mega-projects. The framework is intended for complex programmes where information is abundant but often dispersed across enterprise resource planning systems, planning software, procurement platforms, document environments and supplier reporting.

Aim, Objectives and Review Questions:-

The aim of this review is to develop an evidence-informed framework for integrating cost, schedule and procurement analytics across construction supply chains in Saudi mega-projects to improve forecasting and project delivery under Vision 2030. Four objectives guide the study. First, it examines how cost, schedule and procurement information can be aligned into a common analytical structure. Second, it evaluates predictive methods that support estimate-at-completion, duration, delay and supply-risk forecasting. Third, it identifies procurement responses capable of converting early-warning signals into practical mitigation. Fourth, it defines governance and implementation requirements for reliable, explainable and continuously improving analytics. Three review questions follow. RQ1 asks which data relationships are necessary to connect cost, schedule and procurement status at

package level. RQ2 asks how predictive analytics can generate useful early warnings without creating false precision or excessive alerting. RQ3 asks how procurement teams should use those warnings to improve delivery reliability, cost control and construction supply-chain resilience.

Review Methodology:-

A structured integrative review was used because the research problem spans project controls, construction economics, artificial intelligence, procurement, supply-chain management and digital twins. The evidence window was limited to 2020-2025. Peer-reviewed sources were prioritised where they contributed directly to construction forecasting, project-management analytics, supply-chain modelling, Saudi cost and delay risk, digital-twin integration or procurement decision support. Search concepts combined construction cost prediction, schedule prediction, duration estimation, project controls, artificial intelligence, machine learning, procurement analytics, construction supply chain, resilience, digital twin, Saudi Arabia and Vision 2030. Studies were screened for methodological clarity and relevance to management decisions. Technical papers were included when their methods could plausibly support cost, schedule or procurement control; conceptual discussions without an operational link were given less weight.

The final synthesis used 30 DOI-bearing references from the required publication period. Evidence was coded under six themes: data integration, cost forecasting, schedule forecasting, supply-chain analytics, procurement response and governance. A second interpretive pass examined recurring mechanisms including common coding, timestamp alignment, leading indicators, uncertainty ranges, supplier risk, scenario testing, digital twins, human validation and feedback from actual outcomes. No primary project data were generated and no invented performance gains are reported. International evidence is treated as transferable mechanism-level knowledge rather than proof that identical results would occur on every Saudi mega-project.

Why Cost, Schedule and Procurement Must Be Integrated:-

Project-control systems frequently separate cost, schedule and procurement because each function has distinct professional responsibilities and software. This separation is administratively convenient but analytically weak. Cost forecasts depend on when work will occur; schedules depend on when resources and materials can be obtained; procurement commitments determine both price certainty and delivery constraints. An integrated model therefore requires explicit relationships among the work breakdown structure, cost breakdown structure and procurement package structure. The first linkage is scope. Each procurement package should map to the quantities, design deliverables and schedule activities it enables. If one package supports several work fronts, that relationship should be represented rather than hidden in narrative descriptions. The second linkage is time. Tender issue, bid return, award, design approval, fabrication, shipment and site-required dates should be aligned with the schedule logic. The third linkage is money. Estimate allowances, purchase orders, approved variations, forecast changes and payment milestones should map to the same package. Without these relationships, managers cannot reliably explain whether a cost movement is caused by quantity growth, timing, price, supplier performance or execution productivity.

Saudi evidence on overruns reinforces the need for this integration. Cost and time deviations are associated with interacting contractual, project and managerial factors rather than isolated estimating errors [16,17]. Early-stage risk modelling similarly shows that contract type, project duration, contract value and application of risk-management practices can influence overall cost exposure [18]. These relationships suggest that forecast quality improves when models reflect both project characteristics and evolving execution conditions. Artificial-intelligence research offers methods for analysing such multidimensional data. Comparative cost-prediction studies show that ensemble methods can handle nonlinear variables and missing information more effectively than some traditional approaches [19]. Broader construction reviews identify machine learning, deep learning and computer vision as increasingly important across cost, time, quality and safety management [1-5]. The practical implication is that mega-project forecasting should move from separate point estimates to connected analytical states. An integrated control state should answer five questions for every major package: what was planned, what has been committed, what has physically progressed, what is now expected, and what decision is required. This creates traceability between data and action. A predicted completion delay becomes more meaningful when the system also shows remaining procurement milestones, associated cost exposure and available mitigation options.

Table 1 summarises the principal data domains required for integrated analysis.

Table 1. Integrated data domains for cost-schedule-procurement analytics.

Data domain	Illustrative records	Primary analytical signal	Decision use
Scope & quantities	BOQ, design maturity, approved changes, package boundaries	Quantity growth and scope uncertainty	Cost and procurement baseline
Cost & commercial	Budget, estimate, commitments, variations, payment, forecast	Cost movement, cash-flow pressure, commercial exposure	Estimate-at-completion and contingency
Schedule & progress	Activities, milestones, critical path, float, productivity	Delay probability and time-cost interaction	Completion forecast and recovery priority
Procurement	Tender dates, bid spread, awards, lead times, expediting status	Late award, market uncertainty, package readiness	Tender timing, package sequence, expediting
Supplier & logistics	Capacity, quality, production, shipping, delivery reliability	Supply disruption and substitution difficulty	Supplier risk and alternative sourcing
Digital/site evidence	BIM/digital twin, IoT, installed quantities, verified progress	Difference between reported and physical state	Real-time validation and recalibration

Cost Forecasting as a Dynamic Process:-

Construction cost forecasting is often represented by a single estimate-at-completion, but mega-project cost exposure changes continuously. At concept stage, uncertainty is dominated by scope maturity, design assumptions and market benchmarks. During procurement, tender spread, supplier qualifications and commercial terms become more informative. During execution, quantities, productivity, variations, claims and schedule effects dominate. A single model is unlikely to perform equally well across all stages. Machine-learning research supports the use of adaptive modelling. Elmousalami compared multiple artificial-intelligence techniques for conceptual cost prediction and found that model performance varies according to data structure and algorithm choice [19]. Sharma and colleagues likewise demonstrated machine-learning-based cost prediction and optimisation in construction operations [20]. These studies indicate that algorithms can improve prediction, but they also highlight the importance of feature quality, missing data and model interpretation.

For mega-project controls, the objective should not be the lowest statistical error in isolation. A forecast must be stable enough for governance, explainable enough for commercial challenge and timely enough to influence decisions. Models should therefore present ranges and drivers alongside point estimates. An adverse forecast range driven by commodity escalation requires a different response from one driven by quantity growth or delayed supplier mobilisation. Cost analytics should also distinguish committed and uncommitted exposure. Committed cost is constrained by executed contracts, although change and claim risk remains. Uncommitted cost retains procurement optionality. This distinction is critical because early warning has greater strategic value before commitments are locked. A model that identifies a probable package escalation before tender can support redesign, market engagement or packaging changes; the same signal after award may only support contingency management. Cash-flow forecasting adds another layer. Schedule movement changes the timing of expenditure even when final cost remains unchanged. Procurement analytics should therefore connect forecast final cost with expected cash timing. This helps leadership understand whether a schedule recovery strategy creates short-term financing pressure or whether delayed procurement shifts expenditure beyond planned funding windows.

Schedule Forecasting and Completion Risk:-

Schedule forecasts on mega-projects are vulnerable to optimism, complex dependencies and delayed recognition of emerging constraints. Traditional critical-path methods remain essential because they explain logic and float, but predictive analytics can supplement them by identifying combinations of variables associated with delay.

Construction-duration research increasingly explores machine learning and hybrid deep-learning architectures [8]. These approaches can incorporate project characteristics, sequential information and uncertainty to estimate duration or delay probability. Artificial-intelligence reviews also identify scheduling and time management as mature application areas within construction management [1,2,7]. The analytical opportunity is to use these models as an additional layer around the deterministic programme rather than replacing the schedule network. A useful schedule-warning model should monitor both outcome and mechanism. Outcome indicators include predicted completion date, probability of milestone slippage and forecast float erosion. Mechanism indicators include design release trends, procurement lead-time variance, approval cycles, labour productivity and supplier production progress. This matters because two activities with equal delay probability may require completely different interventions.

Procurement milestones deserve particular attention. Long-lead packages often create hidden schedule exposure because standard programmes may include only a delivery milestone without modelling design approval, shop drawings, manufacturing, inspection, shipping and customs. Integrated analytics should decompose these stages and compare planned versus actual progress. Where supplier data are sparse, the model should show lower confidence rather than silently treating missing information as normal progress. The strongest forecasts combine project logic with empirical data. A critical-path delay should receive higher management priority when supplier performance is deteriorating and alternative sources are limited. Conversely, a statistical anomaly on a non-critical package may not justify escalation if sufficient float and substitution options exist. Prediction should therefore be interpreted through criticality, materiality and controllability.

Procurement Analytics as the Action Layer:-

Procurement converts analytical insight into project intervention. It controls when suppliers enter the delivery system, how risk is allocated, which alternatives remain available and how quickly disruption can be addressed. For this reason, procurement analytics should not stop at spend dashboards or tender cycle metrics. It should evaluate the consequences of procurement choices on cost and schedule. Construction supply-chain research identifies information dispersion, unreliable supply and weak coordination as recurring problems [21]. Quantitative modelling demonstrates that supply-chain decisions can be optimised under uncertain demand, supplier capacity and disruption [22-24]. Back-up sourcing and inventory strategies can improve resilience, although they create their own costs [23,24]. Saudi research on blockchain readiness likewise highlights traceability and supply-chain resilience as relevant priorities for construction networks [26].

An integrated procurement model should classify packages according to value, critical-path exposure, lead time, supplier concentration, substitutability and commercial flexibility. These dimensions determine which mitigation options are realistic. A high-value package with several qualified suppliers may require competitive re-tendering; a unique specialist system may require intensive supplier development and expediting rather than substitution. Tender analytics can also improve forecasting. Bid dispersion provides information about market uncertainty and scope clarity. A wide range of tender prices may indicate inconsistent interpretation, incomplete design or capacity constraints. Linking tender spread to historical package outcomes can help estimate the probability of post-award changes. Procurement cycle time is similarly important: repeated late clarification or approval stages can become a leading indicator of schedule pressure. Package sequencing should be treated dynamically. If the schedule changes, procurement priorities may need to change before the formal baseline is revised. Integrated analytics can identify packages whose required-on-site dates have become more urgent relative to remaining procurement lead time. This enables earlier escalation and prevents teams from managing procurement only against static target dates.

Construction Supply Chains, Resilience and Digital Visibility:-

Mega-project supply chains are vulnerable because they extend beyond the project boundary. Fabrication capacity, raw materials, freight availability, ports, customs, regulatory changes and geopolitical conditions can affect delivery even when site operations are well managed. Resilience is therefore partly a visibility problem and partly an options problem. Systematic construction supply-chain research describes resilience as an emerging management priority supported by organisational, managerial and technological capabilities [21]. Robust optimisation studies show that back-up sourcing and inventory policies can reduce financial exposure to uncertain supply and demand [23]. Scenario-based models similarly show that prequalified alternative suppliers can reduce the cost of responding to disruption [24]. These studies support a practical principle: resilience must be designed before disruption, not improvised after failure. Digital twins can strengthen visibility by linking the physical and digital state of project assets, materials and processes. Construction research shows applications in monitoring, planning, logistics and project control [27-30]. Digital-twin-enabled supply-chain studies specifically identify potential for overcoming

fragmentation and improving integration [24]. The value for integrated project controls is not the three-dimensional representation itself but the capacity to maintain current data relationships and support scenario analysis.

A project-level digital twin could connect approved design, schedule position, procurement status, delivered materials and installed progress. If a package is delayed, the model can test effects on downstream work, cash flow and resource demand. If an alternative supplier is considered, the model can compare lead time, price, logistics and programme consequences. These capabilities turn the digital twin into a decision environment rather than a visualisation product. However, digital visibility is only as reliable as its data. Automated feeds can create false confidence when coding, timestamps or status definitions are inconsistent. Data governance must therefore define ownership, update frequency and validation rules. Manual supplier reports should not be treated as equivalent to verified production milestones without a documented assurance process.

Early-Warning Intelligence and Decision Thresholds:-

Early warning is the mechanism that connects forecasting to management attention. A dashboard can display hundreds of metrics, but an effective warning system distinguishes normal variation from conditions that require intervention. Threshold design therefore matters as much as algorithm design. Warnings should combine probability, impact, time-to-effect and controllability. A package with a modest probability of delay may deserve urgent action when it sits on the critical path and has no substitute. A package with a higher probability may require only monitoring when it has substantial float and multiple supply options. This risk-based logic prevents teams from treating every statistical deviation as equally important.

Confidence should be explicit. Predictive models are subject to error, and uncertainty increases when historical data are sparse or project conditions are novel. Reporting a single completion date or final cost can imply a level of certainty that the evidence does not support. Prediction intervals, probability bands and scenario ranges are more appropriate for major commercial decisions. Explainability supports governance. Project managers need to know which variables contributed to a warning and whether those variables make operational sense. Explainability also helps detect data-quality failures. If a cost-risk score is driven by an incorrect supplier status or outdated quantity record, the appropriate response is to correct the data rather than change the procurement strategy. Recent evidence in project management supports a human-centred interpretation of predictive analytics. Artificial intelligence can improve planning, forecasting, resource allocation and managerial decision support, but professional review remains necessary when outputs influence cost, schedule or procurement commitments [6-9]. Accordingly, early-warning systems should expose their drivers, uncertainty and data lineage so that managers can challenge recommendations before converting analytical signals into formal commercial action.

Integrated Analytics Framework:-

The proposed framework contains six layers. Layer one is integrated project data: estimates, quantities, schedule activities, procurement packages, contracts, supplier records and progress. Layer two aligns this information through common work, cost and package codes, timestamp rules and data-quality checks. Layer three applies predictive analytics to estimate final cost, delay probability, cash flow and supplier risk. Layer four converts predictions into governed early-warning states. Layer five evaluates procurement responses. Layer six captures actual delivery outcomes and feeds them back into forecasting and decision rules. Figure 1 illustrates the end-to-end architecture. It shows that the analytical process begins with integrated project information rather than a model. This is deliberate. Machine learning cannot compensate for inconsistent package identifiers or schedules that are not linked to procurement milestones. Figure 2 presents the framework as a closed-loop operating model. The cycle moves from detection to diagnosis, forecasting, decision, action and learning. Four gates constrain the cycle: data quality, schedule integrity, procurement capacity and management review. These gates recognise that analytics operates inside governance rather than above it.

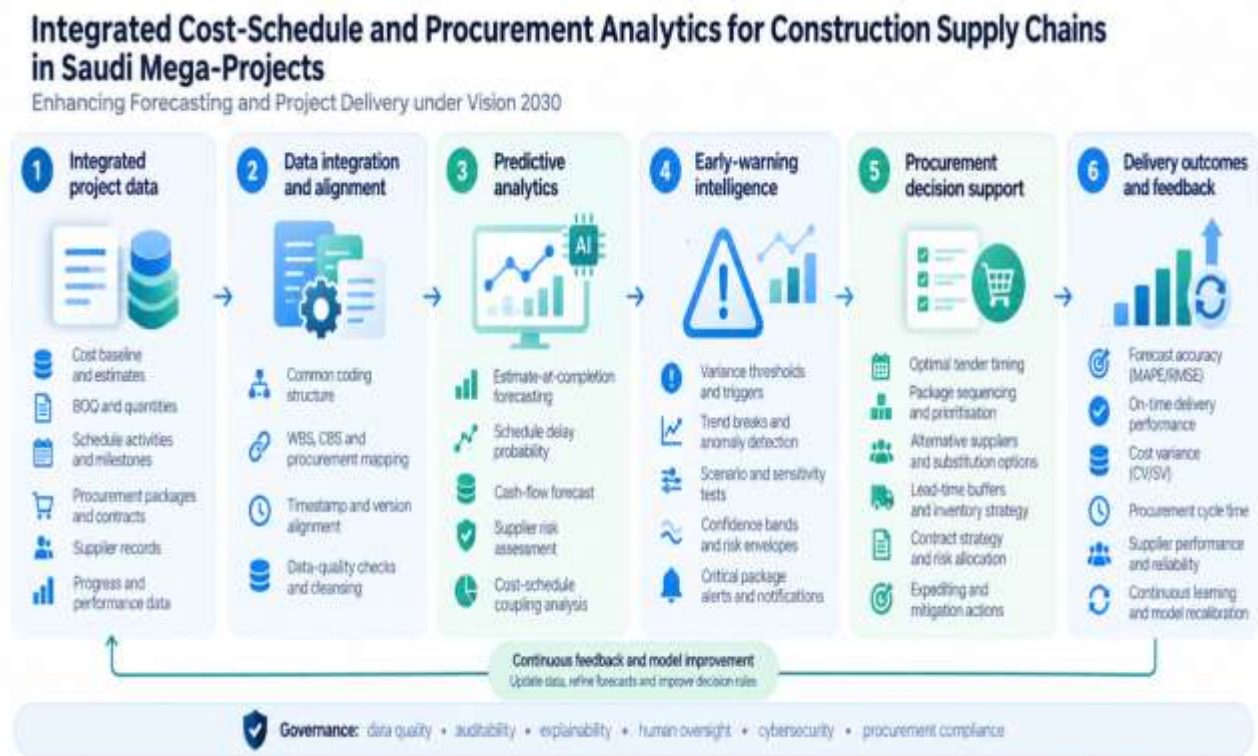


Figure 1. Integrated cost-schedule and procurement analytics architecture for construction supply chains in Saudi mega-projects.



Figure 2. Closed-loop delivery-control model linking detection, diagnosis, forecasting, procurement action and organisational learning.

The framework also distinguishes prediction from decision. The model may predict a delay, but management must determine whether to expedite, resequence, substitute, renegotiate or accept the risk. The correct response depends on commercial rights, supplier capacity, technical approval and project priorities that may not be fully represented in the dataset.

Table 2 translates the framework into governance controls and measurable indicators.

Table 2. Governance gates and performance indicators for integrated analytics.

Gate	Core controls	Primary owner	Illustrative indicators
Data gate	Aligned WBS/CBS/package codes; timestamps; provenance; quality rules	Project controls + data governance	Missing mappings; data freshness; late updates
Forecast gate	Validated cost/schedule models; uncertainty ranges; driver explanations	Analytics + controls leadership	MAE/RMSE; calibration; drift; forecast stability
Schedule gate	Critical-path integrity; milestone logic; procurement dependencies	Planning leadership	Float erosion; completion probability; milestone variance
Procurement gate	Supplier capacity; lead times; substitution options; approval rules	Procurement/commercial leadership	Tender cycle; lead-time risk; mitigation cycle time
Management gate	Materiality thresholds; human review; documented decision rationale	Programme leadership	Warnings acted upon; overdue decisions; override reasons
Learning gate	Actual cost, dates, supplier outcomes and mitigation effectiveness	Integrated controls team	Cost variance; schedule variance; supplier reliability; model improvement

Vision 2030 Relevance and Saudi Implementation:-

Saudi mega-projects provide a strong case for integrated analytics because scale magnifies coordination failures. Large programmes contain repeated package types, multiple delivery partners and extensive supply networks, creating both risk and data-learning opportunities. Historical package performance can support benchmarking, while shared coding standards can enable comparison across workstreams. Vision 2030 alignment should not be reduced to a statement about digital transformation. The relevant contribution is improved delivery capability: better forecast reliability, earlier identification of constraints, stronger supplier coordination and more transparent procurement decisions. These outcomes support capital efficiency and programme accountability.

Implementation should begin with a limited number of critical packages. Organisations should select packages with meaningful cost, schedule and supply-chain exposure, establish reliable data mappings and compare integrated forecasts with existing control methods. Initial models can be transparent rules and statistical baselines. More complex machine learning should be introduced only where it produces measurable improvement. A practical pilot should also establish a decision baseline before advanced analytics is introduced. Existing forecast accuracy, procurement lead times, escalation frequency and mitigation cycle times should be recorded so that improvement can be demonstrated rather than assumed. Data ownership should be assigned at source-system level, with named responsibility for schedule status, cost commitments, supplier milestones and package coding. The pilot should then test whether integrated warnings arrive earlier than conventional reporting and whether managers can act on them. Where warnings are technically correct but operationally unusable, the response should be redesign of the workflow rather than simply retraining the model. This distinction is important because decision latency may be caused by approval structures, contractual constraints or missing supplier alternatives rather than poor prediction. Scaling should occur only after the organisation demonstrates that the analytical signal, governance process and procurement response operate together consistently across several reporting cycles.

Saudi construction research indicates that time and cost overruns remain material concerns [16,17], while supply-chain digitalisation research identifies resilience and traceability opportunities [26]. These findings suggest that implementation should involve project controls, commercial, procurement, logistics and data teams together. A forecasting model owned only by an analytics function is unlikely to change procurement behaviour. Training is equally important. Planners need to understand probability and model uncertainty; procurement professionals need to interpret schedule criticality; commercial teams need to distinguish forecast risk from contractual entitlement; and data specialists need to understand project coding and status logic. Integrated analytics is therefore an organisational capability, not merely a software deployment.

Performance Measurement and Continuous Learning:-

The framework should be evaluated using both predictive and operational measures. Predictive metrics include mean absolute error, root mean squared error, calibration of prediction intervals and classification performance for delay or supplier-risk warnings. Operational metrics include warning lead time, procurement cycle time, proportion of material warnings acted upon, supplier on-time delivery and time required to close mitigation actions. Delivery outcomes should include cost variance, schedule variance, contingency use, change-order frequency and recovery performance after disruption. These measures allow the organisation to test whether better predictions actually lead to better decisions. A model can be statistically accurate yet operationally weak if warnings arrive too late or if no feasible action is available.

Continuous learning requires preserving decision history. Each warning should record the evidence available, the action considered, the decision taken and the eventual outcome. This creates a dataset for evaluating whether thresholds were appropriate and whether certain mitigations consistently outperform others. It also supports auditability when procurement decisions are challenged. Model recalibration should be planned. Mega-project data distributions change as work progresses from civil packages to specialist systems, as market conditions shift and as suppliers learn. Monitoring should therefore track drift in forecast error and warning performance by package type. Recalibration should not be automatic when commercial consequences are significant; updated models should be validated before deployment.

Research Priorities:-

Future research should focus on genuinely integrated datasets rather than separate cost or schedule prediction. Studies are needed that link package-level procurement milestones, supplier performance, schedule logic and commercial exposure over time. Such datasets would allow researchers to test whether integrated models provide earlier and more reliable warning than conventional controls. A second priority is causal evaluation. Many studies show that analytics can predict risk, but fewer demonstrate that specific procurement interventions reduce total project exposure. Research should compare alternatives such as expediting, dual sourcing, inventory buffering and package resequencing while accounting for their cost.

A third priority is Saudi-specific external validation. Models trained on international building datasets may not generalise to giga-project conditions involving remote locations, specialised systems, localisation requirements and high programme interdependence. Validation across Saudi infrastructure, tourism, urban development and industrial projects would improve transferability. Finally, research should examine governance and human behaviour. The success of predictive systems depends on whether managers trust warnings, whether teams act early and whether commercial incentives support transparency. Technical performance is necessary, but organisational response determines whether analytics improves delivery.

Conclusion:-

Integrated cost-schedule and procurement analytics offers a practical route from fragmented project reporting to predictive delivery control. The literature reviewed demonstrates that machine learning can support cost and duration forecasting, construction supply-chain models can quantify disruption and resilience options, and digital twins can connect evolving project states. The main opportunity is to combine these capabilities rather than deploy them separately. For Saudi mega-projects, the analytical unit should increasingly be the procurement package linked simultaneously to scope, cost, schedule, supplier and progress data. This structure allows emerging variance to be diagnosed before it becomes irreversible. Early-warning intelligence can then prioritise material and controllable risks, while procurement teams translate warnings into actions such as earlier tendering, alternative sourcing, expediting, resequencing, inventory buffering or revised contract strategies.

The proposed six-layer framework emphasises that predictive models are only one component of the system. Reliable data alignment, interpretable outputs, governed thresholds, human judgement and feedback from actual outcomes are equally important. The framework is therefore designed as a closed loop in which delivery experience continuously improves forecasts and decision rules. Under Vision 2030, the benefit of this approach is not technology adoption for its own sake. It is stronger project-delivery capability: more dependable forecasts, more coordinated supply chains, more transparent procurement decisions and earlier management action. When cost, schedule and procurement are managed as connected signals within one analytical architecture, Saudi mega-project organisations can shift from explaining variance after the event towards anticipating and managing it before project value is lost. Main-text word count: 4,400 (Abstract through Conclusion, including section headings and in-text citation markers; excluding title, tables, figure captions and references).

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