

Integrated Cost-Schedule and Procurement Analytics for Construction Supply Chains in Saudi Mega-Projects: Enhancing Forecasting and Project Delivery under Vision 2030.

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.

Keywords: cost-schedule integration; procurement analytics; construction supply chain; predictive analytics; Saudi Arabia; mega-projects; project controls; artificial intelligence; Vision 2030

1. 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

65 demonstrate the value of back-up sourcing, inventory strategies, robust optimisation and digital visibility
66 [23-26]. These findings imply that procurement should not be treated only as an administrative
67 purchasing process. It is a control mechanism through which predicted cost and schedule risks can be
68 mitigated.

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

75 **2. Aim, Objectives and Review Questions**

76 The aim of this review is to develop an evidence-informed framework for integrating cost, schedule and
77 procurement analytics across construction supply chains in Saudi mega-projects to improve forecasting
78 and project delivery under Vision 2030.

79 Four objectives guide the study. First, it examines how cost, schedule and procurement information can
80 be aligned into a common analytical structure. Second, it evaluates predictive methods that support
81 estimate-at-completion, duration, delay and supply-risk forecasting. Third, it identifies procurement
82 responses capable of converting early-warning signals into practical mitigation. Fourth, it defines
83 governance and implementation requirements for reliable, explainable and continuously improving
84 analytics.

85 Three review questions follow. RQ1 asks which data relationships are necessary to connect cost,
86 schedule and procurement status at package level. RQ2 asks how predictive analytics can generate
87 useful early warnings without creating false precision or excessive alerting. RQ3 asks how procurement
88 teams should use those warnings to improve delivery reliability, cost control and construction supply-
89 chain resilience.

90 **3. Review Methodology**

91 A structured integrative review was used because the research problem spans project controls,
92 construction economics, artificial intelligence, procurement, supply-chain management and digital twins.
93 The evidence window was limited to 2020-2025. Peer-reviewed sources were prioritised where they
94 contributed directly to construction forecasting, project-management analytics, supply-chain modelling,
95 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.

4. 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

Data domain	Illustrative records	Primary analytical signal	Decision use
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

144

145 5. Cost Forecasting as a Dynamic Process

146 Construction cost forecasting is often represented by a single estimate-at-completion, but mega-project
147 cost exposure changes continuously. At concept stage, uncertainty is dominated by scope maturity,
148 design assumptions and market benchmarks. During procurement, tender spread, supplier qualifications
149 and commercial terms become more informative. During execution, quantities, productivity, variations,
150 claims and schedule effects dominate. A single model is unlikely to perform equally well across all
151 stages.

152 Machine-learning research supports the use of adaptive modelling. Elmousalami compared multiple
153 artificial-intelligence techniques for conceptual cost prediction and found that model performance varies
154 according to data structure and algorithm choice [19]. Sharma and colleagues likewise demonstrated
155 machine-learning-based cost prediction and optimisation in construction operations [20]. These studies
156 indicate that algorithms can improve prediction, but they also highlight the importance of feature
157 quality, missing data and model interpretation.

158 For mega-project controls, the objective should not be the lowest statistical error in isolation. A forecast
159 must be stable enough for governance, explainable enough for commercial challenge and timely enough
160 to influence decisions. Models should therefore present ranges and drivers alongside point estimates. An
161 adverse forecast range driven by commodity escalation requires a different response from one driven by
162 quantity growth or delayed supplier mobilisation.

163 Cost analytics should also distinguish committed and uncommitted exposure. Committed cost is
164 constrained by executed contracts, although change and claim risk remains. Uncommitted cost retains
165 procurement optionality. This distinction is critical because early warning has greater strategic value
166 before commitments are locked. A model that identifies a probable package escalation before tender can

167 support redesign, market engagement or packaging changes; the same signal after award may only
168 support contingency management.

169 Cash-flow forecasting adds another layer. Schedule movement changes the timing of expenditure even
170 when final cost remains unchanged. Procurement analytics should therefore connect forecast final cost
171 with expected cash timing. This helps leadership understand whether a schedule recovery strategy
172 creates short-term financing pressure or whether delayed procurement shifts expenditure beyond planned
173 funding windows.

174 **6. Schedule Forecasting and Completion Risk**

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

179 Construction-duration research increasingly explores machine learning and hybrid deep-learning
180 architectures [8]. These approaches can incorporate project characteristics, sequential information and
181 uncertainty to estimate duration or delay probability. Artificial-intelligence reviews also identify
182 scheduling and time management as mature application areas within construction management [1,2,7].
183 The analytical opportunity is to use these models as an additional layer around the deterministic
184 programme rather than replacing the schedule network.

185 A useful schedule-warning model should monitor both outcome and mechanism. Outcome indicators
186 include predicted completion date, probability of milestone slippage and forecast float erosion.
187 Mechanism indicators include design release trends, procurement lead-time variance, approval cycles,
188 labour productivity and supplier production progress. This matters because two activities with equal
189 delay probability may require completely different interventions.

190 Procurement milestones deserve particular attention. Long-lead packages often create hidden schedule
191 exposure because standard programmes may include only a delivery milestone without modelling design
192 approval, shop drawings, manufacturing, inspection, shipping and customs. Integrated analytics should
193 decompose these stages and compare planned versus actual progress. Where supplier data are sparse, the
194 model should show lower confidence rather than silently treating missing information as normal
195 progress.

196 The strongest forecasts combine project logic with empirical data. A critical-path delay should receive
197 higher management priority when supplier performance is deteriorating and alternative sources are

198 limited. Conversely, a statistical anomaly on a non-critical package may not justify escalation if
199 sufficient float and substitution options exist. Prediction should therefore be interpreted through
200 criticality, materiality and controllability.

201 **7. Procurement Analytics as the Action Layer**

202 Procurement converts analytical insight into project intervention. It controls when suppliers enter the
203 delivery system, how risk is allocated, which alternatives remain available and how quickly disruption
204 can be addressed. For this reason, procurement analytics should not stop at spend dashboards or tender
205 cycle metrics. It should evaluate the consequences of procurement choices on cost and schedule.

206 Construction supply-chain research identifies information dispersion, unreliable supply and weak
207 coordination as recurring problems [21]. Quantitative modelling demonstrates that supply-chain
208 decisions can be optimised under uncertain demand, supplier capacity and disruption [22-24]. Back-up
209 sourcing and inventory strategies can improve resilience, although they create their own costs [23,24].
210 Saudi research on blockchain readiness likewise highlights traceability and supply-chain resilience as
211 relevant priorities for construction networks [26].

212 An integrated procurement model should classify packages according to value, critical-path exposure,
213 lead time, supplier concentration, substitutability and commercial flexibility. These dimensions
214 determine which mitigation options are realistic. A high-value package with several qualified suppliers
215 may require competitive re-tendering; a unique specialist system may require intensive supplier
216 development and expediting rather than substitution.

217 Tender analytics can also improve forecasting. Bid dispersion provides information about market
218 uncertainty and scope clarity. A wide range of tender prices may indicate inconsistent interpretation,
219 incomplete design or capacity constraints. Linking tender spread to historical package outcomes can
220 help estimate the probability of post-award changes. Procurement cycle time is similarly important:
221 repeated late clarification or approval stages can become a leading indicator of schedule pressure.

222 Package sequencing should be treated dynamically. If the schedule changes, procurement priorities may
223 need to change before the formal baseline is revised. Integrated analytics can identify packages whose
224 required-on-site dates have become more urgent relative to remaining procurement lead time. This
225 enables earlier escalation and prevents teams from managing procurement only against static target
226 dates.

8. 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.

9. 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.

257 Warnings should combine probability, impact, time-to-effect and controllability. A package with a
258 modest probability of delay may deserve urgent action when it sits on the critical path and has no
259 substitute. A package with a higher probability may require only monitoring when it has substantial float
260 and multiple supply options. This risk-based logic prevents teams from treating every statistical
261 deviation as equally important.

262 Confidence should be explicit. Predictive models are subject to error, and uncertainty increases when
263 historical data are sparse or project conditions are novel. Reporting a single completion date or final cost
264 can imply a level of certainty that the evidence does not support. Prediction intervals, probability bands
265 and scenario ranges are more appropriate for major commercial decisions.

266 Explainability supports governance. Project managers need to know which variables contributed to a
267 warning and whether those variables make operational sense. Explainability also helps detect data-
268 quality failures. If a cost-risk score is driven by an incorrect supplier status or outdated quantity record,
269 the appropriate response is to correct the data rather than change the procurement strategy.

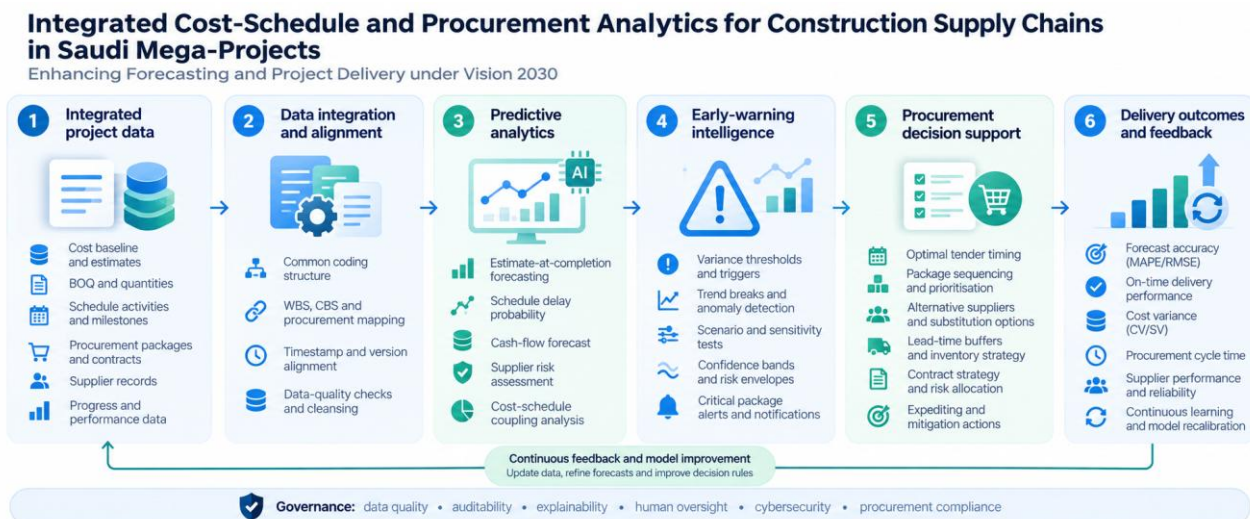
270 Recent evidence in project management supports a human-centred interpretation of predictive analytics.
271 Artificial intelligence can improve planning, forecasting, resource allocation and managerial decision
272 support, but professional review remains necessary when outputs influence cost, schedule or
273 procurement commitments [6-9]. Accordingly, early-warning systems should expose their drivers,
274 uncertainty and data lineage so that managers can challenge recommendations before converting
275 analytical signals into formal commercial action.

276 **10. Integrated Analytics Framework**

277 The proposed framework contains six layers. Layer one is integrated project data: estimates, quantities,
278 schedule activities, procurement packages, contracts, supplier records and progress. Layer two aligns
279 this information through common work, cost and package codes, timestamp rules and data-quality
280 checks. Layer three applies predictive analytics to estimate final cost, delay probability, cash flow and
281 supplier risk. Layer four converts predictions into governed early-warning states. Layer five evaluates
282 procurement responses. Layer six captures actual delivery outcomes and feeds them back into
283 forecasting and decision rules.

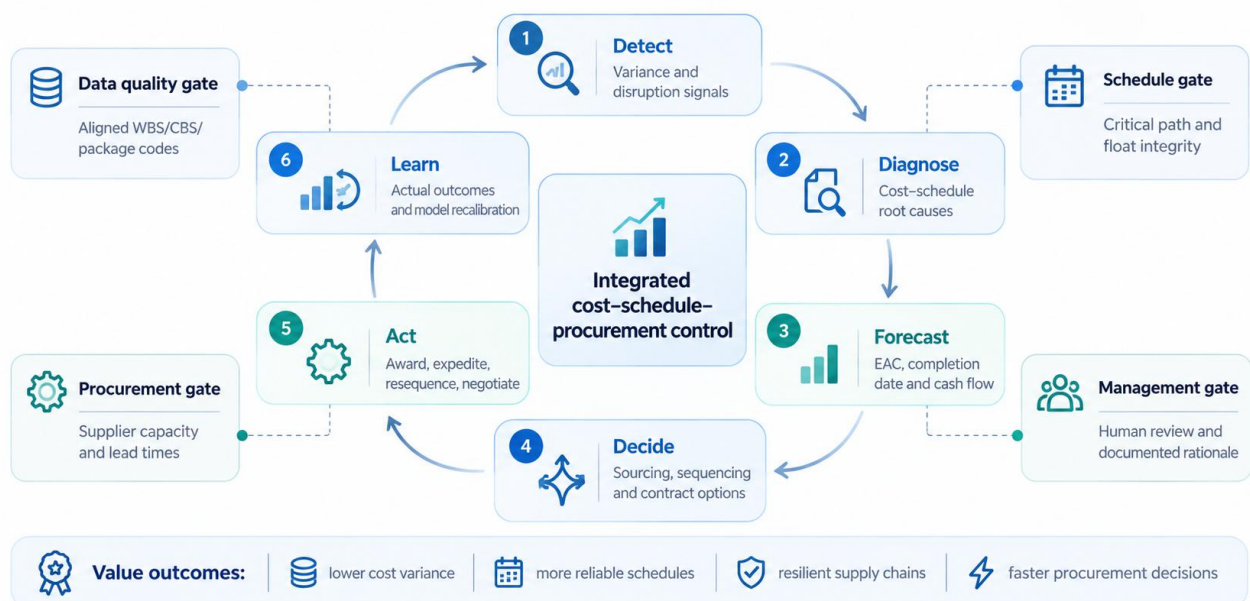
284 Figure 1 illustrates the end-to-end architecture. It shows that the analytical process begins with
285 integrated project information rather than a model. This is deliberate. Machine learning cannot
286 compensate for inconsistent package identifiers or schedules that are not linked to procurement
287 milestones.

288 Figure 2 presents the framework as a closed-loop operating model. The cycle moves from detection to
 289 diagnosis, forecasting, decision, action and learning. Four gates constrain the cycle: data quality,
 290 schedule integrity, procurement capacity and management review. These gates recognise that analytics
 291 operates inside governance rather than above it.



292
 293 *Figure 1. Integrated cost-schedule and procurement analytics architecture for construction supply*
 294 *chains in Saudi mega-projects.*

Closed-loop delivery-control model for Saudi mega-projects



295
 296 *Figure 2. Closed-loop delivery-control model linking detection, diagnosis, forecasting, procurement*
 297 *action and organisational learning.*

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

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

303 **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

305 **11. Vision 2030 Relevance and Saudi Implementation**

306 Saudi mega-projects provide a strong case for integrated analytics because scale magnifies coordination
307 failures. Large programmes contain repeated package types, multiple delivery partners and extensive
308 supply networks, creating both risk and data-learning opportunities. Historical package performance can
309 support benchmarking, while shared coding standards can enable comparison across workstreams.

310 Vision 2030 alignment should not be reduced to a statement about digital transformation. The relevant
311 contribution is improved delivery capability: better forecast reliability, earlier identification of
312 constraints, stronger supplier coordination and more transparent procurement decisions. These outcomes
313 support capital efficiency and programme accountability.

314 Implementation should begin with a limited number of critical packages. Organisations should select
315 packages with meaningful cost, schedule and supply-chain exposure, establish reliable data mappings
316 and compare integrated forecasts with existing control methods. Initial models can be transparent rules
317 and statistical baselines. More complex machine learning should be introduced only where it produces
318 measurable improvement.

319 A practical pilot should also establish a decision baseline before advanced analytics is introduced.
320 Existing forecast accuracy, procurement lead times, escalation frequency and mitigation cycle times
321 should be recorded so that improvement can be demonstrated rather than assumed. Data ownership
322 should be assigned at source-system level, with named responsibility for schedule status, cost
323 commitments, supplier milestones and package coding. The pilot should then test whether integrated
324 warnings arrive earlier than conventional reporting and whether managers can act on them. Where
325 warnings are technically correct but operationally unusable, the response should be redesign of the
326 workflow rather than simply retraining the model. This distinction is important because decision latency
327 may be caused by approval structures, contractual constraints or missing supplier alternatives rather than
328 poor prediction. Scaling should occur only after the organisation demonstrates that the analytical signal,
329 governance process and procurement response operate together consistently across several reporting
330 cycles.

331 Saudi construction research indicates that time and cost overruns remain material concerns [16,17],
332 while supply-chain digitalisation research identifies resilience and traceability opportunities [26]. These
333 findings suggest that implementation should involve project controls, commercial, procurement,
334 logistics and data teams together. A forecasting model owned only by an analytics function is unlikely to
335 change procurement behaviour.

336 Training is equally important. Planners need to understand probability and model uncertainty;
337 procurement professionals need to interpret schedule criticality; commercial teams need to distinguish
338 forecast risk from contractual entitlement; and data specialists need to understand project coding and
339 status logic. Integrated analytics is therefore an organisational capability, not merely a software
340 deployment.

341 **12. Performance Measurement and Continuous Learning**

342 The framework should be evaluated using both predictive and operational measures. Predictive metrics
343 include mean absolute error, root mean squared error, calibration of prediction intervals and
344 classification performance for delay or supplier-risk warnings. Operational metrics include warning lead
345 time, procurement cycle time, proportion of material warnings acted upon, supplier on-time delivery and
346 time required to close mitigation actions.

347 Delivery outcomes should include cost variance, schedule variance, contingency use, change-order
348 frequency and recovery performance after disruption. These measures allow the organisation to test
349 whether better predictions actually lead to better decisions. A model can be statistically accurate yet
350 operationally weak if warnings arrive too late or if no feasible action is available.

351 Continuous learning requires preserving decision history. Each warning should record the evidence
352 available, the action considered, the decision taken and the eventual outcome. This creates a dataset for
353 evaluating whether thresholds were appropriate and whether certain mitigations consistently outperform
354 others. It also supports auditability when procurement decisions are challenged.

355 Model recalibration should be planned. Mega-project data distributions change as work progresses from
356 civil packages to specialist systems, as market conditions shift and as suppliers learn. Monitoring should
357 therefore track drift in forecast error and warning performance by package type. Recalibration should
358 not be automatic when commercial consequences are significant; updated models should be validated
359 before deployment.

360 **13. Research Priorities**

361 Future research should focus on genuinely integrated datasets rather than separate cost or schedule
362 prediction. Studies are needed that link package-level procurement milestones, supplier performance,
363 schedule logic and commercial exposure over time. Such datasets would allow researchers to test
364 whether integrated models provide earlier and more reliable warning than conventional controls.

365 A second priority is causal evaluation. Many studies show that analytics can predict risk, but fewer
366 demonstrate that specific procurement interventions reduce total project exposure. Research should

367 compare alternatives such as expediting, dual sourcing, inventory buffering and package resequencing
368 while accounting for their cost.

369 A third priority is Saudi-specific external validation. Models trained on international building datasets
370 may not generalise to giga-project conditions involving remote locations, specialised systems,
371 localisation requirements and high programme interdependence. Validation across Saudi infrastructure,
372 tourism, urban development and industrial projects would improve transferability.

373 Finally, research should examine governance and human behaviour. The success of predictive systems
374 depends on whether managers trust warnings, whether teams act early and whether commercial
375 incentives support transparency. Technical performance is necessary, but organisational response
376 determines whether analytics improves delivery.

377 **14. Conclusion**

378 Integrated cost-schedule and procurement analytics offers a practical route from fragmented project
379 reporting to predictive delivery control. The literature reviewed demonstrates that machine learning can
380 support cost and duration forecasting, construction supply-chain models can quantify disruption and
381 resilience options, and digital twins can connect evolving project states. The main opportunity is to
382 combine these capabilities rather than deploy them separately.

383 For Saudi mega-projects, the analytical unit should increasingly be the procurement package linked
384 simultaneously to scope, cost, schedule, supplier and progress data. This structure allows emerging
385 variance to be diagnosed before it becomes irreversible. Early-warning intelligence can then prioritise
386 material and controllable risks, while procurement teams translate warnings into actions such as earlier
387 tendering, alternative sourcing, expediting, resequencing, inventory buffering or revised contract
388 strategies.

389 The proposed six-layer framework emphasises that predictive models are only one component of the
390 system. Reliable data alignment, interpretable outputs, governed thresholds, human judgement and
391 feedback from actual outcomes are equally important. The framework is therefore designed as a closed
392 loop in which delivery experience continuously improves forecasts and decision rules.

393 Under Vision 2030, the benefit of this approach is not technology adoption for its own sake. It is
394 stronger project-delivery capability: more dependable forecasts, more coordinated supply chains, more
395 transparent procurement decisions and earlier management action. When cost, schedule and procurement
396 are managed as connected signals within one analytical architecture, Saudi mega-project organisations

397 can shift from explaining variance after the event towards anticipating and managing it before project
398 value is lost.

399 *Main-text word count: 4,400 (Abstract through Conclusion, including section headings and in-text*
400 *citation markers; excluding title, tables, figure captions and references).*

401 **References**

- 402 1. Pan, Y.; Zhang, L. Roles of artificial intelligence in construction engineering and management: A
403 critical review and future trends. *Automation in Construction* 2021, 122, 103517.
404 <https://doi.org/10.1016/j.autcon.2020.103517>
- 405 2. Abioye, S.O.; Oyedele, L.O.; Akanbi, L.; Ajayi, A.; Davila Delgado, J.M.; Bilal, M.; Akinade, O.O.;
406 Ahmed, A. Artificial intelligence in the construction industry: A review of present status,
407 opportunities and future challenges. *Journal of Building Engineering* 2021, 44, 103299.
408 <https://doi.org/10.1016/j.jobe.2021.103299>
- 409 3. Darko, A.; Chan, A.P.C.; Adabre, M.A.; Edwards, D.J.; Hosseini, M.R.; Ameyaw, E.E. Artificial
410 intelligence in the AEC industry: Scientometric analysis and visualization of research activities.
411 *Automation in Construction* 2020, 112, 103081. <https://doi.org/10.1016/j.autcon.2020.103081>
- 412 4. Baduge, S.K.; Thilakarathna, S.; Perera, J.S.; Arashpour, M.; Sharafi, P.; Teodosio, B.; Shringi, A.;
413 Mendis, P. Artificial intelligence and smart vision for building and construction 4.0: Machine and
414 deep learning methods and applications. *Automation in Construction* 2022, 141, 104440.
415 <https://doi.org/10.1016/j.autcon.2022.104440>
- 416 5. Akinosho, T.D.; Oyedele, L.O.; Bilal, M.; Ajayi, A.O.; Davila Delgado, J.M.; Akinade, O.O.; Ahmed,
417 A.A. Deep learning in the construction industry: A review of present status and future innovations.
418 *Journal of Building Engineering* 2020, 32, 101827. <https://doi.org/10.1016/j.jobe.2020.101827>
- 419 6. Fridgeirsson, T.V.; Ingason, H.T.; Jonasson, H.I.; Jonsdottir, H. An authoritative study on the near
420 future effect of artificial intelligence on project management knowledge areas. *Sustainability* 2021,
421 13, 2345. <https://doi.org/10.3390/su13042345>
- 422 7. Kor, M.; Yitmen, I.; Alizadehsalehi, S. An investigation for integration of deep learning and digital
423 twins towards Construction 4.0. *Smart and Sustainable Built Environment* 2023, 12, 461–487.
424 <https://doi.org/10.1108/SASBE-08-2021-0148>
- 425 8. Demiss, B.A.; Elsaigh, W.A. Application of novel hybrid deep learning architectures combining
426 Convolutional Neural Networks and Recurrent Neural Networks: construction duration estimates
427 prediction considering preconstruction uncertainties. *Engineering Research Express* 2024, 6, 032102.
428 <https://doi.org/10.1088/2631-8695/ad6ca7>

- 429 **9.** Taboada, I.; Daneshpajouh, A.; Toledo, N.; de Vass, T. Artificial intelligence enabled project
430 management: A systematic literature review. *Applied Sciences* 2023, 13, 5014.
431 <https://doi.org/10.3390/app13085014>
- 432 **10.** Müller, R.; Locatelli, G.; Holzmann, V.; Nilsson, M.; Sagay, T. Artificial intelligence and project
433 management: Empirical overview, state of the art, and guidelines for future research. *Project*
434 *Management Journal* 2024, 55, 9–15. <https://doi.org/10.1177/87569728231225198>
- 435 **11.** Regona, M.; Yigitcanlar, T.; Hon, C.K.H.; Teo, M. Mapping two decades of AI in construction
436 research: A scientometric analysis from the sustainability and construction phases lenses. *Buildings*
437 2023, 13, 2346. <https://doi.org/10.3390/buildings13092346>
- 438 **12.** Zabala-Vargas, S.; Jaimes-Quintanilla, M.; Jimenez-Barrera, M.H. Big Data, Data Science, and
439 Artificial Intelligence for Project Management in the Architecture, Engineering, and Construction
440 Industry: A Systematic Review. *Buildings* 2023, 13, 2944. <https://doi.org/10.3390/buildings13122944>
- 441 **13.** Adebayo, Y.; Udoh, P.; Kamudyariwa, X.B.; Osobajo, O.A. Artificial Intelligence in Construction
442 Project Management: A Structured Literature Review of Its Evolution in Application and Future
443 Trends. *Digital* 2025, 5, 26. <https://doi.org/10.3390/digital5030026>
- 444 **14.** Barcaui, A.; Monat, A. Who is better in project planning? Generative artificial intelligence or project
445 managers? *Project Leadership and Society* 2023, 4, 100101.
446 <https://doi.org/10.1016/j.plas.2023.100101>
- 447 **15.** Egwim, C.N.; Alaka, H.; Demir, E.; Balogun, H.; Olu-Ajayi, R.; Sulaimon, I.; Wusu, G.; Yusuf, W.;
448 Muideen, A.A. Artificial intelligence in the construction industry: A systematic review of the entire
449 construction value chain lifecycle. *Energies* 2024, 17, 182. <https://doi.org/10.3390/en17010182>
- 450 **16.** Alshihri, S.; Al-Gahtani, K.; Almohsen, A. Risk Factors That Lead to Time and Cost Overruns of
451 Building Projects in Saudi Arabia. *Buildings* 2022, 12, 902.
452 <https://doi.org/10.3390/buildings12070902>
- 453 **17.** Alsugair, A.M. Cost Deviation Model of Construction Projects in Saudi Arabia Using PLS-SEM.
454 *Sustainability* 2022, 14, 16391. <https://doi.org/10.3390/su142416391>
- 455 **18.** Badawy, M.; Alqahtani, F.; Hafez, H. Identifying the risk factors affecting the overall cost risk in
456 residential projects at the early stage. *Ain Shams Engineering Journal* 2022, 13, 101586.
457 <https://doi.org/10.1016/j.asej.2021.09.013>
- 458 **19.** Elmousalami, H.H. Comparison of Artificial Intelligence Techniques for Project Conceptual Cost
459 Prediction: A Case Study and Comparative Analysis. *IEEE Transactions on Engineering Management*
460 2020, 68, 183–196. <https://doi.org/10.1109/TEM.2020.2972078>

- 461 **20.** Sharma, V.; Zaki, M.; Jha, K.N.; Krishnan, N.M.A. Machine Learning-Aided Cost Prediction and
462 Optimization in Construction Operations. *Engineering, Construction and Architectural Management*
463 2022, 29, 1241–1257. <https://doi.org/10.1108/ECAM-10-2020-0778>
- 464 **21.** Liao, L.; Yang, C.; Quan, L. Construction supply chain management: A systematic literature review
465 and future development. *Journal of Cleaner Production* 2023, 382, 135230.
466 <https://doi.org/10.1016/j.jclepro.2022.135230>
- 467 **22.** Chen, Z.; Hammad, A.W.A. Mathematical modelling and simulation in construction supply chain
468 management. *Automation in Construction* 2023, 156, 105147.
469 <https://doi.org/10.1016/j.autcon.2023.105147>
- 470 **23.** Chen, Z.; Hammad, A.W.A.; Alyami, M. Building construction supply chain resilience under supply
471 and demand uncertainties. *Automation in Construction* 2024, 158, 105190.
472 <https://doi.org/10.1016/j.autcon.2023.105190>
- 473 **24.** Bakhshi, S.; Ghaffarianhoseini, A.; Ghaffarianhoseini, A.; Najafi, M.; Rahimian, F.; Park, C.; Lee,
474 D. Digital twin applications for overcoming construction supply chain challenges. *Automation in*
475 *Construction* 2024, 167, 105679. <https://doi.org/10.1016/j.autcon.2024.105679>
- 476 **25.** Badkoubeh, M.; Ghannadpour, S.F. Designing a construction supply chain model using backup
477 supplier aiming at optimizing resiliency against disruption. *Journal of Civil Engineering and*
478 *Management* 2024, 30, 614–631. <https://doi.org/10.3846/jcem.2024.21450>
- 479 **26.** Al Azmi, N.; Sweis, G.; Sweis, R.; Sammour, F. Exploring Implementation of Blockchain for the
480 Supply Chain Resilience and Sustainability of the Construction Industry in Saudi Arabia.
481 *Sustainability* 2022, 14, 6427. <https://doi.org/10.3390/su14116427>
- 482 **27.** Cheng, J.C.P.; Chen, W.; Chen, K.; Wang, Q. Data-driven predictive maintenance planning
483 framework for MEP components based on BIM and IoT using machine learning algorithms.
484 *Automation in Construction* 2020, 112, 103087. <https://doi.org/10.1016/j.autcon.2020.103087>
- 485 **28.** Reja, V.K.; Pradeep, M.S.; Varghese, K. Digital Twins for Construction Project Management (DT-
486 CPM): Applications and Future Research Directions. *Journal of the Institution of Engineers (India):*
487 *Series A* 2024, 105, 793–807. <https://doi.org/10.1007/s40030-024-00810-8>
- 488 **29.** Piras, G.; Muzi, F.; Tiburcio, V.A. Digital Management Methodology for Building Production
489 Optimization through Digital Twin and Artificial Intelligence Integration. *Buildings* 2024, 14, 2110.
490 <https://doi.org/10.3390/buildings14072110>
- 491 **30.** Serugga, J. Digital Twins and AI Decision Models: Advancing Cost Modelling in Off-Site
492 Construction. *Eng* 2025, 6, 22. <https://doi.org/10.3390/eng6020022>