DIGITAL CONSTRUCTION DELAY ANALYSIS

Machine Learning for Construction Delay Prediction in Saudi Arabian Mega-Projects: A Structured Review and Research Agenda Aligned with Vision 2030

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Abstract

Saudi Arabia's Vision 2030 has created one of the largest construction programmes in the world, and delivering it on time is a national priority. Schedule delay has nevertheless been a persistent feature of the Kingdom's construction sector for four decades. Machine learning (ML) offers a way to move from explaining delays after they occur to predicting them while there is still time to act. This paper presents a structured review of published work on ML-based construction delay prediction and of the evidence on delay causes in Saudi Arabia, and derives a research agenda for Saudi mega-projects. The review finds that the causes of delay in the Kingdom are well documented and stable over time, with payment, change-order, planning and workforce factors recurring across studies. ML studies report classification accuracies above 90%, but most are trained on small, questionnaire-derived datasets, are validated internally only, and predict a single static outcome for conventional projects. Only a small number use Saudi project records, and none of the reviewed studies addresses giga-project scale. Seven research priorities are proposed, covering shared project-outcome data, time-dependent prediction from progress records, external validation, explainable models, programme-level interdependence, text-based data sources and the link from prediction to mitigation. Each priority is mapped to the objectives of Vision 2030.

Keywords: construction delay; machine learning; mega-projects; Saudi Arabia; Vision 2030

1 Introduction

Vision 2030 sets out Saudi Arabia's plan to diversify its economy around three themes: a vibrant society, a thriving economy and an ambitious nation [1]. Much of that plan is physical. New cities, tourism destinations, transport networks, housing and social infrastructure all have to be designed and built within a fixed horizon, and their value to the national programme depends on when they open as much as on what they cost.

The scale of this programme is unusual. An industry study reported in 2025 counted 577 major programmes in the Kingdom and a 643% increase in active megaprojects since 2010, attributing the growth to Vision 2030 and to programmes such as Qiddiya, Diriyah and King Salman International Airport; the same study estimated that about 11% of more than 5,000 major programmes examined worldwide were at risk of significant delay or cancellation [2]. The wider megaproject literature has long observed that very large projects are delivered late and over budget far more often than not [3].

Saudi construction entered this period with a documented delay problem. A widely cited survey of the Eastern Province found that 70% of projects experienced time overrun and that 45 of the 76

projects examined were delayed [4]. Later studies of public-sector projects reached similar conclusions about the frequency and length of delays [5], [6]. Most of this research is diagnostic. It ranks the causes of delay as perceived by clients, consultants and contractors, and it has done so consistently for thirty years.

Machine learning changes the question that can be asked. Instead of ranking causes across an industry, a model trained on past projects can estimate the delay risk of a specific project from its characteristics and its progress to date. International studies have applied decision trees, naive Bayes classifiers, random forests, neural networks and ensemble methods to this task [7], [8], [9], and reviews of artificial intelligence in construction identify schedule and delay prediction as an established application area [10], [11], [12].

What is missing is a synthesis that connects these two bodies of work in the Saudi context. This paper addresses three questions. First, what does the published evidence say about the causes of construction delay in Saudi Arabia? Second, how have ML methods been used to predict construction delay, with what data, and how reliable are the reported results? Third, what research is needed before ML-based delay prediction can support the delivery of Saudi mega-projects, and how does that research relate to the objectives of Vision 2030?

The paper makes three contributions. It consolidates the Saudi delay-cause evidence into a form that can inform the choice of predictive features. It compares the ML delay-prediction studies on a common basis of data source, method and validation. It proposes a research agenda that is specific to the Kingdom's mega-project environment.

2 Review method

This is a structured narrative review. Sources were identified in November 2026 through searches of publisher websites, open-access indexes and institutional repositories. Search terms combined the outcome (construction delay, schedule overrun, time overrun, delay risk) with the method (machine learning, artificial intelligence, neural network, random forest, ensemble, explainable) and with the context (Saudi Arabia, Gulf, mega-project, giga-project, Vision 2030). The reference lists of the studies found were then examined for further relevant work.

A source was included if it met one of three conditions: it reported empirical evidence on the causes or extent of delay in Saudi construction projects; it developed or evaluated an ML model whose target was construction delay, delay risk or final duration; or it was a published review of artificial intelligence in construction project management that covered schedule performance. Sources were limited to work in English published between 1995 and 2026. Foundational papers on the ML methods discussed were added for reference.

For each included study, the context, data source, sample size, method, validation approach and headline result were recorded. The review does not claim to be exhaustive, and no bibliographic database was queried through a formal screening protocol. The consequences of this choice are stated in the section on the limitations of this review.

3 Delay in Saudi construction: the evidence base

3.1 Extent of delay

Evidence that Saudi projects finish late goes back to the 1980s. One recent study summarises the record: an early investigation found that close to 70% of projects undertaken by the ministry responsible for housing and public works were delayed, and a later analysis reported that 952 of 2,379 projects, about 40%, experienced delay [13]. The 2006 Eastern Province survey reported time overrun in 70% of projects, with average overruns of between 10% and 30% of the original duration [4].

These figures are dated, and they describe conventional projects delivered under traditional public contracts. They are still the figures on which more recent Saudi studies rely. A 2023 modelling paper, for example, motivates its work with the statistic that only 30% of building projects in the Kingdom finish on time, and its source for that statistic is the 2006 survey [14]. A current, project-level measurement of schedule performance across the Kingdom does not appear in the reviewed literature.

3.2 Causes of delay

The causes have been studied repeatedly. The first systematic survey of large building projects identified 56 causes and examined how contractors, consultants and owners ranked them [15]. A study of public utility projects followed [16]. The 2006 survey found that change orders were the cause most commonly identified by all three parties [4]. A survey of 86 clients, contractors and consultants on public-sector projects organised causes into seven groups relating to the client, contractor, consultant, materials, labour, contract and relationships, and pointed to the shortage of qualified and experienced personnel as a leading influence [5]. A survey of 22 public owners later examined the same problem from the owner's side [17].

More recent work gives a consistent picture. A study of government-funded building projects compiled 83 risk factors in nine categories and found that the most significant contributors to delay were the contractor's financial difficulties, the owner's late progress payments, award to the lowest bidder, change orders during construction, ineffective planning and scheduling by the contractor, manpower shortage and poor site management [6]. A review of Saudi delay studies and a dedicated study of payment delay, which found contractual issues to be the leading cause of late payment on public projects, reinforce these findings [18], [13].

These results are close to the global pattern. A meta-analysis of relative importance index values from international studies identified 36 common causes, and its top five were the contractor's financial difficulties, delay in approval of completed work, slow delivery of materials, poor site organisation and coordination, and poor planning of resources and duration estimation [19].

3.3 Implications for prediction

Three points follow for anyone building a predictive model. The first is that the dominant causes are organisational and financial. They concern payment behaviour, procurement method, the volume of change and the capability of the parties. A model restricted to physical project attributes such as floor area or contract value will not observe them. The second is that almost all of this evidence is perception data gathered by questionnaire. It records what practitioners believe causes delay, which is useful for selecting candidate features and of limited use as training data. The third is that the stability of the findings over thirty years suggests that these factors are structural, and so a model

trained on past Saudi projects should retain some validity for future ones, provided that the project type is comparable.

4 Machine learning approaches to delay prediction

4.1 How the problem is framed

The reviewed studies frame delay prediction in three ways. The most common is classification, in which a project is assigned to a delay-risk class such as low, medium or high [7], [8], [20], [9]. The second is regression, in which the model estimates final duration or the amount of delay [21], [14]. The third is unsupervised analysis, in which delay risk factors are grouped without a target variable [22]. A separate line of project-control research forecasts final duration from periodic earned value data using methods such as support vector regression [23]; it treats prediction as something that is updated during execution and is discussed further in the section on critical gaps.

4.2 Algorithms

Early studies used interpretable classifiers. One trained decision tree and naive Bayes models on a multivariate dataset of past projects' time performance and delay risk sources, and found the naive Bayes model the better of the two [7]. Tree ensembles followed. Random forests aggregate many decision trees trained on resampled data [24], and one study combined a random forest with genetic-algorithm optimisation to predict delay risk [8]. Another compared bagging, boosting and naive Bayes ensembles on expert-survey data from Nigeria and concluded that ensembles outperform single algorithms [9]. Gradient-boosted trees such as XGBoost [25] are now a standard choice for tabular project data and appear in the most recent studies [26], [27].

Neural networks are the other main family. A study of tall building projects compared k-nearest neighbours, artificial neural networks, support vector machines and ensembles and found the neural network to be the most accurate [20]. A deep multilayer perceptron was developed for Iranian dam projects, and its authors found that adding project characteristics to the training data improved prediction markedly [28]. A comparison of twenty-seven algorithms on survey data found a perceptron model to be the best performer [29]. Recurrent architectures such as long short-term memory networks [30] are suited to progress data recorded over time, although their use for construction delay is still limited in the work reviewed here.

4.3 Data sources

The source of the training data matters more than the choice of algorithm, and here the literature divides sharply. One group of studies derives its dataset from questionnaires in which experts rate the likelihood or impact of delay factors [8], [20], [9], [29]. The other, smaller group uses records of completed projects [7], [21], [14], [28], [26]. Sample sizes are modest in both groups. Table 1 shows that the datasets range from 12 cases to 150 projects, and one model was built on 48 questionnaire responses.

The most recent work begins to use unstructured data. A 2026 study of highway earthwork projects combines structured records with text processed by pretrained language models to predict both the type and the duration of delay, and then ranks the predicted risks for management attention [27].

Table 1. Summary of reviewed machine learning studies on construction delay and duration prediction.

Study	Context and data	Method	Reported result
Gondia et al. [7]	Multivariate dataset of past projects' time performance and delay risk sources	Decision tree; naive Bayes	Naive Bayes gave the better predictive performance
Yaseen et al. [8]	Questionnaire quantifying the impact of delay sources on previous projects	Random forest optimised by genetic algorithm (RF-GA)	Accuracy 91.67%; kappa 87%; classification error 8.33%
Sanni-Anibire et al. [21]	High-rise buildings; 12 cases with 9 features	Regression, k-nearest neighbours, neural network, support vector machine; combined models	Best single model R^2 0.56; combined model R^2 0.59
Sanni-Anibire et al. [20]	Tall buildings, Gulf region; 36 risk factors; 48 expert responses	k-nearest neighbours, neural network, support vector machine, ensembles	Neural network accuracy 93.75%
Egwim et al. [9]	Nigeria; expert survey on delay factors	Bagging, boosting and naive Bayes ensembles with hyperparameter optimisation	Ensembles outperformed single algorithms
Egwim and Alaka [29]	Expert survey on delay factors	Comparison of 27 algorithms	Perceptron best; accuracy 85%
Alsugair et al. [14]	Saudi Arabia; 135 completed building projects; inputs were contract cost, contract duration and sector	Artificial neural network predicting final duration	Mean absolute percentage error 12.22% after removal of outliers; 14.92% on test data
Shirazi and Toosi [28]	Iran; dam construction projects	Deep multilayer perceptron	Accuracy 94.36%, as cited in [12]
Al-Bataineh et al. [22]	Indonesia; survey of 68 contracting firms; 60 risk factors	K-means clustering with principal component analysis	Four clusters of delay risk factors
Maurya and Lakkimsetty [26]	India; 150 construction projects	Linear regression, neural network, gradient boosting machine	Accuracy assessed alongside interpretability
Cho et al. [27]	Highway earthwork; structured and unstructured project data	Pretrained language models with ML classifiers; SHAP explanations	Predicts delay type and duration and prioritises risks

4.4 Validation and reported performance

Reported accuracies are high. Three of the classification studies in Table 1 report figures above 90% [8], [20], [28]. These numbers should be read with care, for four reasons.

First, the test sets are small. A model trained and tested on 48 responses is evaluated on a handful of held-out cases, so a single misclassification changes the reported accuracy by several percentage points. Second, validation is internal. As far as could be established from the published descriptions, the studies test their models by cross-validation or on a held-out part of the same dataset, and none reports performance on projects from a different organisation, region or period. Third, where the inputs and the target both come from the same questionnaire, the model learns the relationship between two sets of expert opinions and is not tested against what happened on site. Fourth, results obtained under stricter conditions are less favourable. A recent systematic review notes that the

decision tree and naive Bayes models built on objective data achieved test accuracies of about 47% and 51% [12], and the Saudi duration model required removal of records with large errors before its error fell to about 12% [14].

None of this means that the methods do not work. It means that the published evidence does not yet show how well they work on new projects, which is the condition under which they would be used.

4.5 Explainability

A project director who is told that a package has a high probability of delay needs to know why. Shapley additive explanations (SHAP) attribute a model's prediction to its input features and have become the usual tool for this purpose [31]. Recent delay-prediction studies integrate SHAP so that each prediction is accompanied by its main drivers [27], and a study of Indian projects treats the balance between accuracy and interpretability as a design objective [26]. A PRISMA-based review of delay risk drivers for BIM-based projects complements this work by identifying the drivers that such models should take as inputs [32].

4.6 Saudi-specific studies

Few of the reviewed studies use Saudi data. The duration model trained on 135 completed building projects is the clearest example [14]. A framework developed by researchers based in the Kingdom applies ML to cost estimation, duration estimation and delay risk assessment within the CRISP-DM process and was validated through interviews with industry experts [33]; its delay risk component rests on the 48-response dataset noted above [20]. A recent doctoral study uses random forest, gradient boosting and ridge regression to rank the determinants of cost, schedule and scope outcomes in Saudi project delivery [34]. All of these concern conventional building or infrastructure projects. No study in the reviewed set develops or tests a delay-prediction model on a Saudi mega-project or giga-project.

5 Critical gaps

5.1 Data

The first gap is data. The field depends on small samples and on opinion surveys, and there is no shared repository of project outcomes for the Kingdom. The digital foundation for collecting such data is still forming: building information modelling is described as relatively new in the Saudi building sector, and its adoption depends on awareness and on leadership from both government and industry [35].

5.2 Evaluation

The second gap is evaluation. Without external or temporal validation, reported accuracy is an upper bound. Reviews of the field note that proof-of-concept validation and limited generalisability are recurring barriers [12].

5.3 Static prediction

The third gap is that most models make one prediction from attributes known at the start. Delay develops during execution, and its dominant causes in the Saudi evidence, such as late payment, change orders and slow approvals, arise during execution as well. Project-control research shows

that forecasts can be updated from periodic progress data [23], yet delay-risk classification studies seldom use such data.

5.4 Scale and interdependence

The fourth gap is scale. A giga-project is a programme of hundreds of contracts that share logistics, labour, utilities and approvals. Delay in one package propagates to others. Models that treat each project as an independent observation cannot represent this, and the megaproject literature indicates that very large projects behave differently from the conventional projects on which existing models are trained [3].

5.5 From prediction to action

The fifth gap is use. A recent systematic review concludes that the translation of prediction results into proactive time management remains underexplored [12]. Only the most recent work links prediction to the prioritisation of responses [27].

6 Research agenda for Saudi mega-projects

The gaps above suggest seven research priorities. Table 2 maps each to the objective of Vision 2030 that it serves [1].

Priority 1 is a national project-outcome dataset. Public owners and programme developers hold schedule baselines, progress updates and completion records for thousands of contracts. A common schema for anonymised schedule outcomes, covering planned and actual dates, contract type, procurement route, change-order volume, payment history and approval durations, would give researchers the objective data that current studies lack. The features should be chosen to capture the causes that the Saudi literature has identified [4], [6], [13].

Priority 2 is time-dependent prediction. Models should be retrained or updated at each reporting period using progress, payment and change data, so that risk estimates reflect the project as it is and not only as it was planned. Sequence models [30] and periodically refitted gradient-boosted models [25] are both candidates, and the comparison between them on Saudi progress data is an open empirical question.

Priority 3 is validation that matches use. Studies should report performance on projects that were completed after the training data were collected and on projects from organisations not represented in training. Accuracy alone is insufficient where delayed projects are the majority class; recall for the delayed class, calibration of predicted probabilities and lead time before the delay becomes visible are more informative.

Priority 4 is explainable output. Each prediction should identify the factors that drive it, using methods such as SHAP [31], so that the responsible party can be engaged. Because the leading Saudi delay causes are attributable to specific parties, explanation is also a matter of contractual fairness.

Priority 5 is programme-level modelling. Research is needed on representing dependencies between packages, shared resources and common approval bodies, for example through network or graph-based features, so that the risk of one contract reflects the state of those it depends on.

Priority 6 is the use of text. Site diaries, correspondence, meeting minutes and notices of claim contain early signals of delay. Language-model methods have been demonstrated on highway projects

[27]. Their application to Saudi project documents, which are commonly bilingual in Arabic and English, has not been reported in the reviewed literature.

Priority 7 is decision support. Predictions should be connected to defined responses, such as accelerating an approval, releasing a payment or re-sequencing work, and studies should measure whether projects that use the predictions perform better than those that do not.

Table 2. Research priorities and their alignment with Vision 2030.

Research priority	Gap addressed	Alignment with Vision 2030
1. National project-outcome dataset	Small samples and reliance on opinion surveys	Ambitious nation: effective, transparent and data-driven government
2. Time-dependent prediction from progress records	Static, one-time prediction	Thriving economy: timely delivery of giga-projects and infrastructure
3. External and temporal validation	Internal validation only	Ambitious nation: efficient public spending through reliable forecasts
4. Explainable models	Opaque predictions that are hard to act on	Ambitious nation: accountability among project parties
5. Programme-level interdependence	Projects treated as independent observations	Thriving economy: coordinated delivery of large development programmes
6. Text-based data sources, including Arabic	Unused site and contract documents	Thriving economy: digital transformation and local technology capability
7. Link from prediction to mitigation	Prediction not connected to decisions	Vibrant society: housing and public facilities available when planned

These priorities also fit the way the Kingdom's programme is organised. A limited number of large public owners and developers commission most of the work, which makes common data standards more attainable than in a fragmented market. The same owners can require that delay-prediction outputs are reported alongside conventional schedule updates, which would generate the evidence on usefulness that Priority 7 calls for.

7 Limitations of this review

Three limitations should be noted. The search was not conducted through a formal database protocol, so relevant studies may have been missed and the counts given here should not be read as a census of the field. For several studies behind publisher paywalls, the synthesis relies on abstracts and bibliographic records; details such as sample composition could not always be confirmed. The megaproject figures in the introduction come from an industry study as reported in the press and not from a peer-reviewed source. The conclusions about gaps are therefore statements about the reviewed literature. A systematic review conducted through Scopus or Web of Science with a documented screening process would be a useful extension.

8 Conclusion

The causes of construction delay in Saudi Arabia have been documented consistently since the 1990s, and they are dominated by payment, change, planning and capability factors that arise during execution. Machine learning studies show that delay risk can be modelled, yet their evidence rests

largely on small, survey-based datasets validated internally, and very little of it comes from Saudi projects or from projects at giga-project scale. The value of ML for Vision 2030 delivery will depend less on the choice of algorithm than on three things: objective project-outcome data shared across owners, models that update as a project progresses, and evaluation on projects that the model has not seen. The seven priorities set out in this paper are intended to guide that work.

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