The Future of Risk Mitigation in Procurement: Contractor Prequalification

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***Abstract* — This paper discusses risk mitigation in procurement and how this could evolve over the next decade because of advances in Artificial Intelligence (AI) applications. The paper includes a literature review that covers contractors' prequalification as a common measure for risk mitigation, a brief non-technical introduction to AI, and the previous research related to the application of AI in contractors' prequalification. The paper expounds the current practice of contractor prequalification and reveals some of the current deficiencies in manual evaluation and the previously proposed AI models. The paper reports the results of examining the correlation between the contractor's prequalification's and performance of 34 contractors where no significant correlation is noticed. The paper demonstrates that Machine Learning (ML) and Natural Language Processing (NLP) could potentially overcome some of these deficiencies. Finally, the paper proposes a framework in which AI can assist risk mitigation in procurement.**

Keywords — *Contractor Prequalification, Artificial Intelligence, Machine Learning (ML), Contractor Performance, Risk Management*

1. Introduction

Whenever a contract is awarded, there is invariably the risk that the contractor may fail to deliver upon the expectations within the established criteria. Consequently, a number of measures are commonly taken during the procurement process to mitigate the risk of awarding the contract to a contractor who may fail to deliver as expected. Typically, prequalification evaluation is conducted to ensure that the bidder who is invited to participate in the bidding is capable of delivering upon the requirements of the contract. In some organizations (buyer/clients), a prequalification evaluation is conducted that covers the contractor's accumulated experience, reputation, past performance, financial stability, current workload, the firm's resource capacity, financial/technical capabilities [4], and other aspects of technical expertise. Conversely, other organizations conduct several independent evaluations during the procurement process.

These could include a technical prequalification that assesses the technical capabilities of the bidder, a financial evaluation that assesses the financial capabilities, and a safety evaluation to assess the contractor's safety practices, along with other relevant elements. In addition, a technical proposal could be required for submission, along with the commercial proposal, which is usually relevant to the scope of the work to be procured.

Currently, most organizations employ their personnel to conduct the contractor prequalification. However assiduously this is carried out, and regardless of the risk of human bias, the prequalification may prove to be fruitless and the prequalified contractors may fail to deliver, as is highlighted in this paper.

Since the 1980s, researchers have tried to use AI algorithms to conduct contractors' prequalification. Most of this research was more theoretical and academic in nature and the practical tools proved to be difficult to implement within industry. However, the recent advances in algorithms, data availability, and affordable computational power (graphics processing units, GPUs) have provided a new paradigm for employing AI in contractors' prequalification [13]. Indeed, AI solutions appear to be able to carry out this task more reliably than human beings.

The main purpose of this paper is to demonstrate the potential evolution of contractors' prequalification through employing AI. The paper sets out the challenges and limitations of the conventional manual prequalification process for contractors. The paper also proposes a feasible framework for a dynamic risk management solution that employs machine learning (ML) and natural language processing (NLP).

2. Literature Review

2.1 Contractor Prequalification

Contractor prequalification evaluation revolves mainly around what is a risk to the buyer. The risks may include non-physical attributes such as environmental, social, and ethical impacts, as well as integrity, security, and organizational behavior issues.

The elements that are evaluated during the prequalification evaluation may be classified as critical and non-critical. Usually, critical elements are mandatory, while non-critical elements may be discretionary. Typically, the buyer evaluates the following items:

- Organizational profile
- Contractor's technical capabilities (previous experience)
- Contractor's capacity (resources)
- Financial capabilities
- Health and safety
- Quality management
- Environmental management
- Data Protection

It is not necessary for all of these elements to be evaluated. However, some buyers may add elements, depending on what they may consider as essential or an extra source of risk.

Commonly, the prequalification process is conducted via a questionnaire sent to the bidders, which asks for various items of information. Experienced professionals who have the expertise to review and evaluate the prequalification proposal should carry out the evaluation, having previously established criteria for evaluation to eliminate any subjectivity in the process.

The prequalification questionnaire may cover both quantitative and qualitative data, which should be evaluated objectively. The evaluation scoring system may award a pass/fail or assign weights (points) to each item. Under the pass/fail system, the assumption is that all elements are essential, whereas a point-scoring system distributes the points based upon the criticality of each element. The latter system should be applied cautiously; otherwise, there is a risk that the evaluation will be misleading – especially when there is one comprehensive prequalification that covers multiple critical elements, such as technical, safety, and financial capabilities. It is also expected that the evaluation team verify the accuracy of the information provided by the contractor, which may mandate a site visit.

2.2 Previous Research in AI and Contractor Prequalification

AI may be described as intelligence demonstrated by machines or a computer with cognitive capabilities that can mimic human intelligence. AI may also be seen as an umbrella over various techniques and requirements, including ML and NLP.

AI is a concept that goes back to the 1950s. However, after 2010, AI entered a new era, largely because of the advent of the internet, the availability of data (big data), and increases in computational power and storage capacities, accompanied by a sharp decrease in costs. In addition, the development of ready-made algorithms has driven advances in AI applications.
There have been extensive studies and numerous attempts to apply AI in contractor prequalification evaluation. In the 1980s and 1990s, the focus was on employing expert systems [11]. However, expert systems were developed based on a set of rules (if–then–else) devised by human beings, which limits creativity and the flexibility to adapt to changes. In the 1990s, AI algorithms progressed and researchers explored Case-Based-Reasoning (CBR), which attempts to provide a solution based on another solution for a previous similar problem. Accordingly, a conceptual framework based on CBR for conducting contractor prequalification was proposed [7].

However, contractor prequalification is nonlinear, uncertain, and subjective, which makes the process of evaluation more of an art than a science [5] This led researchers to explore fuzzy logic (fuzzy sets theory), which is a statistical tool that considers uncertainty. Fuzzy logic is thus suitable for handling nonlinear problems and quantitative data, since it allows the processing of linguistic terms, rather than crisp values. In 2009, a contractor evaluation model based on fuzzy sets theory was proposed, which depends on assigned weights of criteria and objectives [8].

In 2000, artificial neural networks (ANNs) as a model for conducting contractor prequalification was experimented [4]. ANNs are data-driven, selfadaptive methods, requiring few assumptions about the problem under study. For example, an ANN eliminates the need for the evaluator to directly assign specific weights to each of the prequalification criteria. Such weights are generally prone to uncertainties and inaccuracies, which can be reduced to the lowest level by neural network models, since the question of whether or not the prequalification decisions are correct will already have been verified in the collected real prequalification cases (training data). This work was one of the first attempts to employ ML as a tool to conduct contractor prequalification. They used 112 real prequalification cases for training and 88 hypothetical prequalification cases for validating the neural network. In 2001, an improved hybrid model that uses ANN and fuzzy logic (FANN) was proposed [5].

In 2009, the support vector machine (SVM) as a method of conducting contractor prequalification was explored. The SVM model, like the neural network-based techniques, involves training and testing of data, where the training set is comprised of target outcome variable(s). The major advantages of SVM include a capacity for strong inference, fast learning, and generalization and the ability to make accurate predictions. SVM is one of the supervised ML methods in which the input data (training) should be labeled with the correct answer. On the other hand, an unsupervised ML algorithm will take the input data and conduct analysis to learn more about the structure of the data. An unsupervised ML technique can provide clustering or association among variables [6

In 2011, a fuzzy analytical hierarchy process (FAHP) model to conduct contractor prequalification was experimented [10}. The analytical hierarchy process (AHP) is a multi-criteria decision technique that uses hierarchical structures to define a problem and then develop priorities for the alternatives. However, AHP is unable to adequately handle inherent uncertainty and imprecision associated with the mapping of the decision-maker's perception to exact numbers. The conventional AHP approach may not fully reflect a style of human thinking, because the decision-maker usually feels more confident to give judgments in the form of intervals rather than single numerical values. Therefore, the FAHP model has the advantage of being able to capture a person's appraisal of ambiguity when complex, multi-criteria, decision-making problems are concerned [10].

In 2020, a hybrid AI model called integrative random forest classifier with genetic algorithm optimization (RF-GA) for delay problem prediction, which is a major risk in any project, was experimented. While the genetic algorithm is a popular technique for optimizing problems in complex systems, RF is a tool that is used to train dataset samples and construct multiple random trees. RF-GA is a popular technique used to optimize problems in complex systems based on natural selection data collected from previous projects to determine delay factors. The RF-GA model has been tested against performance measure indices, demonstrating that it has a better performance than the RF model, including being able to handle the nonlinearity and complexity of data more accurately [12].

3. Deficiencies of Prequalification Models

The literature in this field reveals that treating the evaluation criteria and the contractor's performance independently can defeat the main purpose of prequalification, which is to mitigate the risk of the contractor's failure. Even when a thorough prequalification evaluation has been carried out, there is always a risk that the performance of the contractor will turn out to be below expectations. In 2013, it was reported that, between 2006 and 2010, 35% of contractors who were awarded road construction contracts in Sri Lanka failed to fulfil the project's objectives, although these contractors received high grades in the prequalification evaluation [2]. In addition, the Surety and Fidelity Association of America reported that 29.3% of building, heavy/highway, and specialty trade contractors failed in 2014, although the report does not refer to prequalification [9]. This raises a question about the effectiveness of the contractor prequalification process and whether the elements of the prequalification criteria cover all sources of potential risks. The present authors tested the relationship between the contractor's prequalification evaluation and performance, as illustrated below.

The prequalification evaluation questionnaire is based on assumptions that certain elements constitute potential risks to the contractor's success in meeting the terms and conditions of the contract. The evaluation criteria rely on the perceptions of the subject matter experts, which may not necessarily be a reflection of reality. Whenever a task is carried out by people, there is always a concern about human bias.

Without establishing a correlation between the prequalification evaluation and the contractor's actual performance, the prequalification evaluation will continue to be static and its effectiveness will be questionable. To date, there have been few studies of the relationship between the contractor's prequalification and the performance. Indeed, there may be other elements that are not contained in the evaluation that can lead to the contractor's failure. These include factors beyond the contractor's control, such as eco-political aspects, but this does not diminish skepticism about the reliability of the evaluation. Another challenge is that only one prequalified bidder out of the pool of bidders (prequalified and disqualified) is given the opportunity to perform, which makes establishing a meaningful correlation difficult. Nevertheless, the prequalification evaluation criteria based on actual performance need to be improved so as to have a reliable prequalification model.

Another issue with the prequalification evaluation is determining the weight of each element. Whether the evaluators are using a linguistic method (e.g., good, very good, average, poor) or a point-scoring system, the distribution of the weights (points) for the evaluated elements in the prequalification may be unrealistic and hence unreliable. However, this challenge could be overcome by using supervised ML (e.g., the vector space model, VSM), which has the advantage that there is no need to assume a certain weight for each element.

Treating the prequalification elements as independent variables may not be the best approach. The final output of the prequalification process is to determine whether a contractor is prequalified or disqualified, while the input is a set of elements to be assessed. However, the evaluation elements may be interdependent. Identifying the dependency among the evaluation elements and taking them into consideration could improve the efficiency of the prequalification evaluation.

Prequalification is a snapshot of the contractor at any given time, whereas changes (internal or external) are likely to affect the contractor's performance. Therefore, it is useful for the buyer to monitor the contractor during the execution of the contract to detect any potential risks before they occur and to take proactive prevention measures. Having this capability will provide an effective risk management tool.

It may be implausible to meet these challenges manually. AI, on the other hand, may expedite the prequalification evaluation process, which can be cumbersome, as well as providing new dimensions that are inconceivable without it.

Most of the research conducted before 2012 was academic, and the outcomes were difficult to implement in the industry, mainly because of the immaturity of the computing capabilities. Progress in AI in general, such as the availability of software for various AI algorithms, the increase in computational power, and cloud solutions over the past last eight years have made it more conceivable to have an autonomous contractor prequalification solution. One of the AI areas in which significant progress has been made is NPL, which provides the capability for reviewing natural language documents, especially since Google released bidirectional encoder representations from transformers (BERT) in 2018. For example, resumés and reports, such as safety manuals or quantity management manuals, could be reviewed via software [14].

4. Contractor's Prequalification and Performance

To test whether there is a correlation between the contractor's prequalification and performance, the authors compiled data from 34 contracts for major projects valued at $100 million or more in the last 10 years. The projects were either completed or in the final stage of completion. The collected data for each project included average actual performance, the evaluation of prequalification proposals, and the evaluation of technical proposals. Table I presents the data regression analysis for the 34 contracts, gauging the relationship between the actual performance for the contractor in a specific contract and the contractor's prequalification and technical evaluations.

Table I, below, indicates that there is no significant relationship between the actual performance and the prequalification or technical proposal score (significance F = 0.2766 and $\alpha = 0.05$).

Table I: Summary Output for Performance (SPE), Prequalification (PQQ) and Technical (TP) Evaluations

Summary Output SPE and PQQ & TP

0.05

Regression Statistics	
Multiple R	0.282070737
R Square	0.079563901
Adjusted R Square	0.020180927
Standard Error	11.07417384

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	2	328.6296852	164.3148426	1.339843648	0.276631397
Residual	31	3801.757115	122.6373263		*Not Significant*
Total	33	4130.3868			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	123.1865721	40.09972325	3.072005544	0.004402633	41.40264736	204.9704969	41.40264736	204.9704969
PQQ Score	-0.101305376	0.275043462	-0.368324976	0.715134272	-0.662260215	0.459649462	-0.662260215	0.459649462
TP Score	-0.691623181	0.439659239	-1.573089156	0.125850151	-1.58831411	0.205067748	-1.58831411	0.205067748

Summary Output SPE and PQQ

Regression Statistics	
Multiple R	0.078032461
R Square	0.006089065
Adjusted R Square	-0.024970652
Standard Error	11.3264577

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	1	25.15019328	25.15019328	0.1960438	0.660911991
Residual	32	4105.236607	128.288644		*Not Significant*
Total	33	4130.3868			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	70.6523369	22.7030398	3.112021011	0.00389424	24.40775812	116.8969157	24.40775812	116.8969157
PQQ Score	-0.124377633	0.280909051	-0.442768337	0.660911991	-0.696570647	0.44781538	-0.696570647	0.44781538

Summary Output SPE and TP

Regression Statistics	
Multiple R	0.274837872
R Square	0.075535856
Adjusted R Square	0.046646351
Standard Error	10.92359044

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	1	311.9923023	311.9923023	2.614646988	0.115698118
Residual	32	3818.394498	119.3248281		*Not Significant*
Total	33	4130.3868			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	115.7082296	34.10940719	3.392267386	0.001860975	46.22964075	185.1868184	46.22964075	185.1868184
TP Score	-0.700258587	0.43306383	-1.616987009	0.115698118	-1.582380742	0.181863568	-1.582380742	0.181863568

Table II shows, below, the 10 categories of the performance evaluation for the selected 34 contracts, which has an average of 59.78%. The questionnaire was accompanied by a quick survey of construction managers in the selected companies. The results show that Project Control, Subcontracting, and Materials Procurement are the most challenging categories in the construction phase.

Table II. Supplier Performance Evaluation (SPE%)

Performance Categories	**Weighted Average**
1. Project Control (Schedule)	51.65
2. Local Sourcing	55.04
3. Material Procurement	55.89
4. Subcontracting	56.11
5. Management	57.28
6. Engineering & Design	57.39
7. Human Resources	60.70
8. Equipment & Facility	63.08
9. Project Quality	68.79
10. Project Safety	71.90
Average % for 34 contracts	59.78%

The Project Control category includes schedule control, cost control, and risk management. Materials procurement includes materials selection and expediting and handling, testing, and storage. The Subcontracting category includes subcontracting management and primary and secondary subcontractors.

The results of the present study support those of the study reported in 2013 in Sri Lanka [2], where approximately 30 to 35% of contractors failed to fulfil the project objectives, even though they were technically prequalified.

5. Proposed Framework to Develop a Smart Risk Management Solution

This paper has reviewed contractors' prequalification and the attempts by researchers to employ AI concepts in the process, mentioning some of the challenges and deficiencies with the process and previous proposed solutions. It is evident that, in order to employ AI in contractor prequalification, the solution should be robust, reliable, and friendly, so that it will be accepted by the industry.

Accordingly, the authors propose to develop a contractors' risk management solution with the following features:

1. The solution should be web-based, so that bidders can submit their proposals online.
2. Supervised ML should be implemented to conduct the prequalification.
3. NPL could be employed to evaluate documents such as resumés and quality management manuals.
4. The correlation between the prequalification evaluation of previous procurements and the evaluation of performance, notably including analysis of poor performance, should be realized to form the basis for training data.
5. During the execution of the contract, the contractor should provide real-time information relevant to its financial status and other factors, to enable the detection of any potential risk of the contractor's failure.
6. The performance evaluation elements should, at least to a certain extent, match the prequalification elements.

Such a solution is feasible thanks to the availability and maturity of the technology. It would be even more effective if several buyers aligned themselves and decided upon one cloud solution and one prequalification model. This could help to improve both the prequalification and the performance, since it would yield an enormous amount of data available for training.

6. Conclusions

This paper revealed certain deficiencies with the current manual contractor's prequalification evaluation process as a means of mitigating the risk of the contractor's failure to perform. The paper examined the correlation between contractors' prequalification and performance of 34 mega projects and found no significant correlation. The paper demonstrated that ML and NPL could potentially overcome some of these deficiencies. The prequalification evaluation could be automated, running without human intervention. A dynamic solution could be developed in which the contractor's performance might feed in to the improvement of the prequalification evaluation. In addition, real-time risk monitoring is recommended to monitor the contractor during the execution of the contract.

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References

[1] Acheamfour, VK, Kissi, E, Adjei-Kumi, T and Adinyira, E (2019) Review of empirical arguments on contractor pre-qualification criteria. *Journal of Engineering Design and Technology*. Available online at: https://www.researchgate.net/publication/335453107_Review_of_empirical_arguments_on_contractor_pre-qualification_criteria

[2] Benaragama, HG and Jalyalal, S (2013) Exploring the suitability of Artificial Intelligence for establishing criteria for prequalification of highway contractors in Sri Lanka. IEEE 8th International Conference on

Information Systems (ICIIS), August 18–20. BSI PAS 7000:2014 Supply chain risk management – Supplier prequalification. Available online at: https://www.bsigroup.com/Global/Headers/PAS%207000_book-marked.pdf

[3] Federation of European Risk Management Associations (FERMA), Artificial Intelligence Applied to Risk Management Report. Available online: https://www.eciia.eu/wp-content/uploads/2019/11/FERMA-AI-applied-to-RM-FINAL.pdf

[4] Lam, KC, Ng, ST, Hu, T and Skitmore, M (2000) Decision support system for contractor prequalification: artificial neural network model. *Journal of Engineering, Construction & Architectural Management* 7(3):251-266. Available online at: https://eprints.qut.edu.au/29551/1/c29551.pdf

[5] Lam, KC, Hu, T, Ng, S, Skitmore, M and Cheung, SO (2001) A fuzzy neural network approach for contractor prequalification. *Construction Management and Economics*, 19(2):175-188. Available online at: https://www.researchgate.net/publication/24077500_A_fuzzy_neural_network_approach_for_contractor_prequalification

[6] Lam, KC, Palaneeswaran, E and Yu, C (2009) A support vector machine for contractor prequalification. *Journal of Automation in Construction* 28:321-329. Available online at: http://read.pudn.com/downloads150/ebook/651242/4.pdf

[7] Ng, ST, Smith, NJ and Skitmore, M (1995) Case-based reasoning for contractor prequalification: a feasibility study. The Fourth International Conference on the Application of Artificial Intelligence to Civil and Structural Engineering. Available online at: https://www.researchgate.net/publication/269153410_Case-Based_Reasoning_for_Contractor_Prequalification_-_A_Feasibility_Study

[8] Plebankiewicz, E (2009) Contractor prequalification model using fuzzy set. *Journal of Civil Engineering and Management* 15(4):377-385. Available online at:https://www.researchgate.net/publication/238112712_Contractor_prequalification_model_using_fuzzy_sets

[9] The Surety & Fidelity Association of America. Why do contractors fail? Available online at https://cdn.ymaws.com/www.surety.org/resource/resmgr/learnaboutsurety/why_do_contractors_fail.pdf

[10] Trivedi, MK, Pandey, MK and Bhadoria, S (2011) Prequalification of construction contractor using A FAHP. *International Journal of Computer Applications* 28(10). Available online at: https://www.ijcaonline.org/volume28/number10/pxc3874773.pdf

[11] Yang, J, Li, H and Skitmore, M (1996) Expert systems in construction management: Is the hype over? Proceedings of INCIT 96, International Construction Information Technology Conference (pp. 131-136), The Institution of Engineers Australia. Available online at: https://eprints.qut.edu.au/4546/1/4546.pdf

[12] Bakry, I and Daoud, E (2019) “Contractor Prequalification Model for Lean Project Delivery” *International Journal of Supply Chain Management* 8(4), August 2019

[13] Adeleke, A.Q, Bahaaudin, A.Y, Kamaruddeen, Bamgbade, J.A, Khan, M.W, Panda,S and Afolabi, Y.A (2019) “ An Empirical Analysis of Organizational External Factors on Construction Risk management” *International Journal of Supply Chain Management* 8(1), February 2019

[14] M.A.Al-Sinan and Z. Aljaroudi, "Autonomous Procurement System (APS): Pro Forma Development," 2020 International Conference on Artificial Intelligence & Modern Assistive Technology (ICAIMAT), Riyadh, Saudi Arabia, 2020, pp. 1-6, doi: 10.1109/ICAIMAT51101.2020.9308015. Jan 1, 2021 IEEE Explore