EPiC Series in Built Environment
Volume 7, 2026, Pages 743–752
Proceedings of Associated Schools of Construction 62nd Annual International Conference

Automated Request for Proposal (RFP) Review for Bid/No-Bid Decision-Making using Multi-Criteria Decision-Making

Manish Lal Pradhan[1], Kofi A.B Asare[1], Somik Ghosh[1], Ben Bigelow[1]
[1]The University of Oklahoma

This study explores how to automate the process of RFP reviews for specialty contractors in making their bid/no-bid decisions efficiently. Specialty contractors typically rely on their intuition and experience to make bidding decisions. Making such decisions when faced with choosing multiple project opportunities can be particularly taxing for small-sized specialty contractors who usually have few people assigned to do this task. They often have to rely on consultants for bid document preparation, which comes at a premium. This study addresses this challenge by prototyping and testing a web application that uses a Multi-Criteria Decision-Making method's (MCDM) Weighted Sum Model (WSM), to make reviews faster and more objective. This enables users to assign weight values to each bidding factor, extracted from existing literature. The system then automatically calculates a WSM score for each RFP, then normalizes the score to the range of 0 to 100. The solution, deployed as a web app, provides specialty contractors with a low-cost, instantly deployable tool that reduces the time and effort needed to screen RFPs. This enables them to focus on core operations and respond quickly to opportunities, while advancing knowledge on automated RFP review using MCDM and natural language processing by computers.

Keywords: RFP, Weighted Sum Model, Multi-Criteria Decision-Making, Digital Construction, AI

Introduction

In the construction industry, contracts are secured through competitive bidding, a widely accepted method by clients in both public and private sectors, where the primary basis for selection is often the lowest bid price (Cheng et al., 2011). This process involves contractors making two crucial decisions in sequence: firstly, deciding whether to participate in bidding for a project, and secondly, determining the bid amount to submit (Ahmed et al., 2024). The initial choice of whether to bid is a common and complex task, requiring contractors to simultaneously consider numerous factors related to the project, client, market, and competition (El-Mashaleh, 2013). Preparing the bid proposal is time- and labor-intensive, with multiple steps such as RFP review, feasibility analysis, and preparation of documents with stringent timelines. These processes demand significant resources and often lead to suboptimal submissions due to short bidding windows and limited information (Kwasafo et al., 2025). Despite the importance of this decision, the industry frequently relies on subjective approaches. Deciding to bid involves complexities that go beyond relying solely on intuition, yet studies show that intuition is the most common method used (Cheng et al., 2011). A study conducted by Chisala (2017) reveals that a vast majority (97.5%) of contractors surveyed depend on intuition, a mix of experience and guesswork, as their main tool, while only a small percentage (17.6%) utilize a structured model to aid their decision-making. This highlights a significant gap between the complexity of decisions and the informal methods typically employed to address them (Chisala, 2017). Considering the time and labor overheads and the prevailing subjectivity, automating the process has become a favorable option. However, subjective decision-making is challenging for computer-based systems, as tacit knowledge and situational awareness that human experts possess are difficult to program. Therefore, a systematic and objective approach is needed. To address the limitations of intuition-based bidding decisions and the problem of labor and time intensity in the construction industry, this study proposes a structured framework that leverages artificial intelligence (AI) and MCDM techniques. MCDM provides a structured way to evaluate alternatives against established criteria (Zhu et al., 2021), while AI helps automate the review process.

This research contributes to the domain of applied construction science by codifying tacit, intuition-based review processes into machine-readable, actionable criteria. Building upon foundational MCDM research that established the theoretical basis for decision analysis, this study focuses on the practical operationalization of the WSM into an accessible, low-code artifact. By demonstrating how unstructured RFP data can be automatically parsed and mapped to decision factors, this work bridges the gap between established decision theory and the operational needs of specialty contractors.

Literature Review

Overview of Competitive Bidding in the Construction Industry

In the US construction industry, especially in public projects, contracts are commonly awarded through a competitive bidding process, with the lowest bidder commonly awarded the contract (Ahmed et al., 2022). To enhance transparency and accountability in the allocation of government contracts, competitive bidding is legally mandated in US public construction projects to ensure prudent use of public resources and mitigate risks (Ahmed et al., 2024). *"Competitive bidding is a transparent procurement method in which bids from competing contractors, suppliers, or vendors are invited by openly advertising the scope, specifications, and terms and conditions of the proposed contract; as well as the criteria by which the bids will be evaluated.*"(Ballesteros-Pérez et al., 2013, p.3). Within the context of competitive bidding, the decision to submit a bid represents a critical and recurring strategic choice for construction firms, as most of their projects are secured through this mechanism, yet only a small proportion of the submitted bids are won (Oo et al., 2022). While current data is nonexistent, historically, major construction firms in the US and globally typically win only 15 – 25% of bids submitted (McKinsey & Company, 2017). The actual costs and profits are only realized upon project completion (Takano et al., 2014). The long-run profitability and sustainability of contractors depend primarily on winning the contracts (Drew et al., 2001). Therefore, the bid/no-bid decision is vital for contractors in competitive bidding. Contractors must carefully evaluate multiple bidding factors to decide whether to submit a bid or not. They must also carefully evaluate the potential advantages and viability of pursuing each construction project. A single objective (lowest price) bidding approach is not optimal for the sustainability and profitability of the company. On the other hand, the MCDM approach would better reflect the complex factors influencing bidding success. By evaluating bids through a balanced set of criteria rather than focusing solely on price, contractors can make more informed and strategic decisions.

Competitive Bidding Strategy Model and MCDM

Research on competitive bidding strategy has evolved substantially since the 1950s, progressing from probability-based models to multi-criteria and AI-driven decision methods. Friedman (1956) highlighted five strategic objectives for a contractor: maximizing profits, gaining return on investment, minimizing losses, decreasing competitors' profit, and obtaining a contract even at a loss to maintain continuity of work. Friedman used a probabilistic method to determine the probability of being the lowest and optimum bid. Building on Friedman (1956)'s work, Gates (1967) pioneered a decision theory approach by integrating profit maximization and probability of winning. However, Ballesteros-Pérez et al. (2023) addressed two main issues with Gates' (1967) work: (i) estimation of the probability of a bidder finishing in positions other than first, and (ii) adaptability to situations with incomplete historical information. Rothkopf (1969) extended this line of research by explicitly modelling uncertainty in bidders' own cost estimates. As research progressed, researchers recognized that bidding decisions involve qualitative and quantitative factors. Mustafa & Ryan (1990) were among the first to demonstrate the ability of Analytic Hierarchy Process (AHP) to handle bid evaluation decisions by incorporating both qualitative and quantitative factors, focusing on subcontractors. Ahmad (1990) presented a technique to quantify the subjective evaluation for bid/no-bid decision making based on the decision analysis cycle. Egemen and Mohamed (2007) characterized bidding as a complex decision-making process that requires the simultaneous evaluation of numerous highly interrelated variables. This points out the need to have factors that influence the bid/no-bid decision-making. Bageis & Fortune (2009) found that contractor size, contractor classification status, and contractor and client type had the most weighted importance out of all the identified bid/ no-bid factors. Chisala (2017) developed a structured Simple Additive Weighted Scoring (SAWS) model to assign relative weight to bidding factors, which can evaluate real-life bidding cases. Xiao et al. (2020) address bid evaluation in large-scale group decision-making (LSGDM) contexts, involving expert classification, consensus-reaching processes, and ranking-oriented decision methods such as K-means clustering, hesitant fuzzy linguistic term sets, and ELECTRE III to manage expert input and derive bidder rankings. More recent publications from Xiao et al. (2020), Zhu et al. (2021), and Ahmed et al. (2024) demonstrate the shift to advanced techniques like cluster analysis, fuzzy logic, and AI-based predictive modeling.

Automating Decision-Making in Construction Business

The integration of web services, decision support systems (DSS), and advanced bidding strategies alongside rule-based expert systems, knowledge-based frameworks, and AI-driven optimization algorithms is increasingly shaping automation of decision-making processes in the construction industry (Cusumano et al., 2022; Dickson et al., 2013; Ekström & Björnsson, 2000; Pakgohar et al., 2013; Choi et al., 2021; Lu et al., 2022). The systematic expert knowledge and inference systems can streamline important tasks such as bidding, scheduling, and resource deployment, leading to greater consistency and lower human error. However, the challenges with data integration and project-specific customization requirements exist (Cusumano et al., 2022; Ekström & Björnsson, 2000). Ekström & Björnsson (2000) and Pakgohar et al. (2013) highlight the growing role of mathematical models and neural networks in automating complex decision processes and resource allocation, with their success depending on the availability of quality training data and effective contextual adaptation. These studies highlight the clear shift in the construction industry from manual, experience-based approaches to advanced data-driven automated systems.

AI-enabled Task Automation

AI is fundamentally reshaping how organizations automate routine and complex tasks across construction, business, and research domains (Abioye et al., 2021). AI can now automate key construction processes such as scheduling, bidding, project monitoring, safety inspection, and quality control (Abioye et al., 2021). According to Majeed (2025), AI-enabled knowledge and task automation enhance employee adaptive performance and organizational agility, particularly in the retail industry, by allowing intelligent agents to support employees through rapid document analysis, operational data extraction, and process optimization. These technologies seamlessly integrate into daily workflows, facilitating fast, data-driven decision support, and automated reporting (Majeed, 2025). AI is increasingly playing a core role in advancing bid automation through mediating more efficient, effective, and flexible bidding processes with advanced machine learning and natural language technologies (Kwasafo et al., 2025).

Methodology

This paper presents the early findings of an ongoing Design Science Research (DSR) project focused on developing and validating the web-based decision support application to automate the RFP review process for specialty contractors. DSR is a problem-solving approach that advances human knowledge through the creation of innovative solutions (Vom Brocke et al., 2020). The DSR framework comprises five sequential stages: (1) Awareness of the Problem, (2) Suggestion of Solution, (3) Development of Solution, (4) Evaluation of Solution, and (5) Conclusion and Knowledge Contribution (Venable et al., 2017). In this study, the problem awareness emerged from practical industry needs identified in competitive bidding, particularly in the case of specialty contractors. They lack dedicated personnel, specialized bid evaluation tools, and sufficient organizational capacity to systematically assess RFPs, resulting in time-intensive, labor-dependent bid/no-bid decisions. The solution leveraged existing knowledge from literature on MCDM and natural language processing to propose an automated decision-support system. The current paper reports on the development and formative evaluation phases, with summative evaluation (testing with specialty contractors) planned for subsequent research. The research is organized into three sequential steps: (1) Literature Review for Identification of MCDM Method and Bidding Factors, (2) Web Application Design and Development, and (3) Testing and Initial Evaluation.

Literature Review for Identification of MCDM Method and Bidding Factors

A systematic literature review was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to ensure transparency, reproducibility, and comprehensive coverage of relevant studies.

Database Selection and Search Strategy

Two primary academic databases were queried: Web of Science and Google Scholar. These platforms were selected for their comprehensive coverage of peer-reviewed construction, engineering, and management literature. The search was conducted between 1950 - 2025, using Boolean operators to target the intersection of competitive bidding, multi-criteria decision-making, and automation in construction. The literature search was limited to publications dated between 1950 and 2025 to capture foundational bidding strategy models, the evolution of multi-criteria decision-making (MCDM) frameworks, and automation using AI in decision-making within the construction industry.

Search Query Logic: Primary terms: “competitive bidding in construction” AND “bid/no-bid decision making”. Secondary intersection: “multi-criteria decision-making” OR “MCDM" OR "weighted sum model". Tertiary terms: “automation” OR “decision support”. Combined: “competitive bidding” AND “MCDM OR weighted sum model OR decision-making" AND “construction”).

Inclusion and Exclusion Criteria: The inclusion criteria focused on selecting journal articles and conference proceedings. Only English-language publications were considered, and selected studies needed to show direct relevance to construction bid/no-bid decision factors or the application of MCDM methodologies to construction problems. Conversely, the exclusion criteria removed blog posts and editorial opinions from consideration. Non-English publications, studies focused solely on construction project success metrics that did not address bid decision-making, and gray literature or industry reports lacking methodological transparency were also excluded, with exceptions granted to authoritative reports from organizations like McKinsey & Company provided explicit caveats were used. Duplicate or near-duplicate publications were omitted to maintain the integrity of the review.

Bidding Factors: Prior studies have identified a vast array of decision criteria; for instance, Ahmed et al. (2024) cataloged 43 distinct bidding factors. To ensure the feasibility of the AI extraction module, this study filtered this list to prioritize quantifiable attributes suitable for automation. Table 1 summarizes the subset of six factors selected for the system's architectural design. It is important to note that while the full conceptual framework incorporates all six factors, the current prototype iteration specifically operationalizes the three primary quantitative drivers: Project Budget, Project Size, and Location to establish the baseline for the weighted scoring logic.

Table 1. List of Bidding Factors

Group	**Bidding Factors**	**Description**
Project related factors	Size of the project	The project size in terms of the amount of work and its estimated cost.
	Duration of the project	The estimated project duration, its beginning, and its targeted completion date.
	Location of the project	The location of the project and associated restrictions on that area, whether the company has ongoing or finished projects nearby, and so on.
	Type of contract	The type of the contract, whether it is a lump sum, unit rate, cost plus, or something else.
	Type of project delivery method	The project delivery method, whether it is design-bid-build (DBB), design build (DB), construction manager at risk (CMAR), or something else.
Bidding environment-related factors	Bidding duration	The duration allowed for bid preparation.

Source: Adapted from Ahmed et al. (2024)

Note: While Ahmed et al. (2024) conceptualized 'Size of the project' as a composite of both cost and volume, this study operationalizes them as two distinct variables, Project Budget ($) and Project Size (Sq. Ft), to allow for more granular risk weighting in the decision matrix.

Web Application Design and Development

The web application tool employs the MCDM approach, specifically the WSM, to rank RFPs based on user-defined weights assigned to various bidding factors.

Development Platform and Justification: The web application prototype was developed on the Replit platform (**https://replit.com**), chosen for four key reasons:

- Rapid prototyping capability: Web-based Python/JavaScript environment enabling real-time code execution and testing without local development infrastructure setup.
- AI-assisted coding: Replit's built-in AI coding assistant (Code Completion Agent) accelerates feature development through natural language prompts.
- Deployment readiness: Rapid cloud deployment of prototypes for formative testing.
- Accessibility: Low technical barrier for future user testing and iterative refinement.

Prompt-Driven Development Methodology: Core application features were iteratively constructed using AI-assisted prompting, employing zero-shot prompting.

Zero-Shot Prompting: Zero-shot prompting involves instructing a large language model (LLM) to perform a task based only on the provided instructions, without any examples. In prototyping the web-app, uncontextualized requests describing desired functionality were used for initial feature ideation and rapid prototyping.

System Architecture and Components

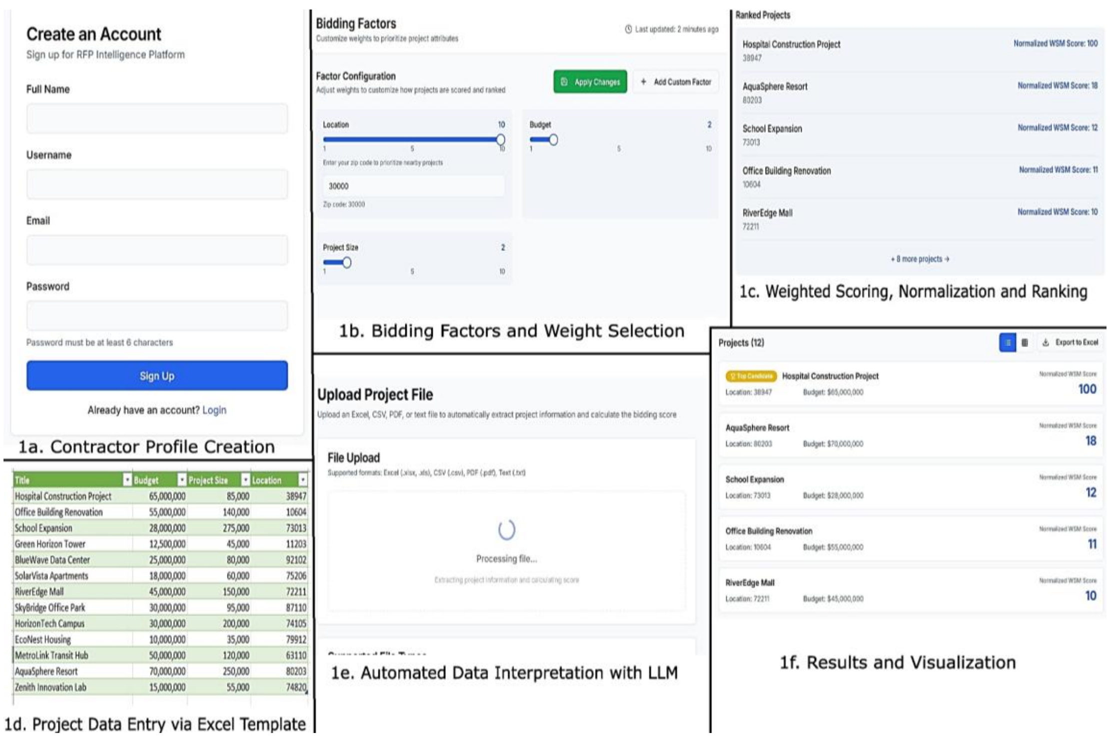

Figure 1: Web App Features

The web application comprises six features (Figure 1):

1. **Contractor Profile Setup:** Each contractor can set up their own profile within the system.
2. **Project Data Entry via Excel Template:** Contractors collect project data via project overview and fill up the existing fields such as project title, budget, size and location. Once the template is filled with multiple project information, it can be uploaded to the web-app.
3. **Bidding Factor Weight Selection:** After uploading the project data, contractors can adjust the importance(weights) assigned to each bidding factor.
4. **Automated Data Interpretation via LLM:** The system processes uploaded project information using OpenAI's GPT-5 model.

5. **Weighted Scoring, Normalization and Ranking:** The system computes a WSM score, which is then normalized to lie on a 0–100 scale. Projects are automatically ranked by their WSM Score for bidding, with those closer to 100 being more preferred than those near zero.

$$\text{WSM Score i} = \sum_{i=1}^{n} xij \cdot wj$$

Where:

i. WSM Score *i* = Total score for each RFP *i*
ii. *wj* = Weight assigned to factor *j*
iii. *xij* = Performance/value of RFP *i* on factor *j*
iv. *n* = Total number of factors

Min – Max Normalization: Different project factors may have ranges that are not directly comparable (e.g., budgets could be \$10M–\$100M, while project durations might be 30–900 days). Normalized Value = $\frac{xij - \min(xj)}{max\,(xj) - min\,(xj)}$x 100

Where,

v. xij = Performance/value of RFP *i* on factor *j*
vi. min(xj)= minimum value observed for factor j across all projects
vii. max(xj)= maximum value observed for factor j across all projects

6. **Results and Visualization:** Contractors will be able to immediately see their projects ranked by score. The results can be viewed through a dashboard.

Testing and Initial Evaluation

The project is in an early prototype phase. To validate the system's logic, an Excel template was populated with a synthetic dataset comprising 13 hypothetical construction projects (Figure 1d). Each project entry included realistic details across all required fields, such as project title, budget, size, and location. This approach allowed for controlled testing of the system's logic and robustness across a diverse range of bidding scenarios. The simulated Excel file was then uploaded to the web app. The system parsed structured and text fields from each entry, applying natural language processing techniques to extract and interpret qualitative project descriptions. All numerical data was normalized to ensure comparability between projects. The web app applied user-defined factor weights and computed a WSM score for each project, automatically scaling scores to a 0–100 range. Projects were then ranked by their scores with results displayed on an ordered table. Testing focused on confirming that the simulated information was correctly processed, factor weights and normalization were accurately applied, and the output rankings reflected logical evaluation of project. Only simulated data was used at this stage; further testing with real projects will be undertaken in subsequent phases.

Discussion

The current work provides a prototype system that integrates (i) automated data extraction based on a LLM; GPT-5, and (ii) a MCDM scoring process based on the WSM methodology. The results from this preliminary testing indicate that it is feasible to implement WSM based approach that allows for quick bid/no-bid decisions based on an objective, yet user-definable, scoring scheme that can standardize a variety of attributes related to an RFP.

Implication for Practice

For specialty contractors, the main technical implication is the potential for improved efficiencies within early-stage RFP screening. Although the existing prototype does not yet automate data extraction from raw documents, it streamlines the comparison process through a structured workflow. First, the process requires users to input specific project metrics (e.g., Project Budget, Location, and

Size) into a standardized template. Second, based on these inputs, the system scores and ranks the projects, effectively narrowing down the candidates for further human attention. Third, this automated filtering saves significant time by identifying and discarding projects that do not align with the contractor's selected bidding factor criteria, allowing them to focus their detailed review efforts solely on opportunities that match their strategic goals and expertise. This process can be considered useful in comparison to extracting project information manually since it helps in decreasing the amount of time needed to reform information for comparison.

Limitation

This study has several limitations consistent with an early-stage prototype and formative evaluation. First, this prototype does not currently allow projects to be automatically extracted from RFPs. It requires users to put together a template and then enter this information into the template which has to be uploaded to the web-based application. Second, the assessment is based on simulated data and technical validation of the scoring process. Although the scenarios were modeled after typical bidding issues, they fail to incorporate real-world. This means the results of the simulated test may not be generalizable. Third, the empirical foundation for practical inferences is limited. Only four exploratory case-study interviews are conducted for this research, which are initially informative but not representative from which inferences based on generalizations are made. Finally, this work does not benchmark the approach against alternative decision models or against baseline manual workflows using standardized accuracy, reliability, and usability measures. Thus, these findings can only imply potential or conceptual ability regarding possible enhancements at this point.

Future Work

Future work will evaluate the tool using more specialty contractors with real RFP documents and screening tasks. We will analyze how different sets of weights impact the ranking to give contractors an idea of how reliable the outcome is. Lastly, we will implement the extraction of information pertaining to the RFP documents to automatically fill out the template verifiable by users.

Conclusion

This study presents an early development and formative evaluation of an RFP review tool designed to assist specialty contractors in automating bid/no-bid decisions. Based on competitive bidding literature and MCDM methodologies, the prototype allows contractors to upload project data via a standardized template, customize bidding factors weights, and receive objective ranked recommendations. Initial technical verification using simulated project data indicated that the system functions according to its design specifications. It successfully parsed the structured excel template inputs, applied normalization and weighting logic, and generated interpretable rankings. By offering a structured alternative that allows contractors to explicitly define their preferences, the tool aims to balance the industry's heavy reliance on intuition with objective scoring. Preliminary results suggest that the tool has the potential to improve decision consistency and streamline the RFP review process. A projected benefit of this automation is the reduction of manual effort for specialty contractors, who often face resource constraints regarding in-house estimation and bid management. This research seeks to demonstrate the feasibility of codifying subjective expert intuition into machine-readable logic by verifying that an AI-driven artifact replicates human ranking logic in a controlled simulation.

References

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Davila Delgado, J. M., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities, and future challenges. *Journal of Building Engineering*, *44*, 103299. https://doi.org/10.1016/j.jobe.2021.103299

Ahmed, M. O., El-adaway, I. H., & Caldwell, A. (2024). *Comprehensive Understanding of Factors Impacting Competitive Construction Bidding*. https://doi.org/10.1061/JCEMD4.COENG-14090

Ahmed, M. O., El-Adaway, I. H., & Coatney, K. (2022). Mitigating the Winner's Curse Dilemma in Multi-Stage Construction Bidding. *Construction Research Congress 2022*, 835–844. https://doi.org/10.1061/9780784483978.085

Alkhateeb, A. M., Hyari, K. H., & Hiyassat, M. A. (2020). Analyzing bidding competitiveness and success rate of contractors competing for public construction projects. *Construction Innovation*, *21*(4), 576–591. https://doi.org/10.1108/CI-04-2020-0060

Anbari Moghadam, M., & Besiktepe, D. (2025). Synthesis of Multi-Criteria Decision-Making Applications in Facilities Management and Building Maintenance: Trends, Methods, and Future Research Directions. *Buildings*, *15*(18), 3258. https://doi.org/10.3390/buildings15183258

Ioannou, P. G., & Leu, S. (1993). Average-Bid Method—Competitive Bidding Strategy. *Journal of Construction Engineering and Management*, *119*(1), 131–147. https://doi.org/10.1061/(asce)0733-9364(1993)119:1(131)

Bageis, A. S., & Fortune, C. (2009). Factors affecting the bid/no bid decision in the Saudi Arabian construction contractors. *Construction Management & Economics*, *27*(1), 53–71. https://doi.org/10.1080/01446190802596220

Ballesteros-Pérez, P., González-Cruz, M. C., & Cañavate-Grimal, A. (2013). On competitive bidding: Scoring and position probability graphs. *International Journal of Project Management*, *31*(3), 434–448. https://doi.org/10.1016/j.ijproman.2012.09.012

Ballesteros-Pérez, P., Skitmore, M., Cerezo-Narváez, A., Otero-Mateo, M., & Pastor-Fernández, A. (2023). Gates' bidding model (revisited). *Construction Management & Economics*, *41*(7), 576–586. https://doi.org/10.1080/01446193.2023.2181980

Cheng, M.-Y., Hsiang, C.-C., Tsai, H.-C., & Do, H.-L. (2011). Bidding decision making for construction company using a multi-criteria prospect model. *Journal of Civil Engineering and Management*, *17*(3), 424–436. https://doi.org/10.3846/13923730.2011.598337

Chisala, M. L. (2017). Quantitative Bid or No-Bid Decision-Support Model for Contractors. *Journal of Construction Engineering and Management*, *143*(12), 04017088. https://doi.org/10.1061/(asce)co.1943-7862.0001407

Chiu, D. K. W., Ng, N. L. L., Lai, S. C., Farwick, M., & Hung, P. C. K. (2013). *Automating Tendering Processes with Web Services: A Case Study on Building Construction Tendering in Hong Kong*. https://doi.org/10.1007/978-1-4614-7535-4_13

Choi, S. J., Choi, S. W., Kim, J. H., & Lee, E.-B. (2021). AI and Text-Mining Applications for Analyzing Contractor's Risk in Invitation to Bid (ITB) and Contracts for Engineering Procurement and Construction (EPC) Projects. *Energies*, *14*(15), 4632. https://doi.org/10.3390/en14154632

Cusumano, L., Saraiva, R., Rasmus Rempling, Jockwer, R., & Granath, M. (2022). Intelligent building contract tendering – potential and exploration. *IABSE Symposium Report*, 1902–1909. https://doi.org/10.2749/prague.2022.1902

Ahmad, I. (1990). Decision-Support System for Modeling Bid/No-Bid Decision Problem. *Journal of Construction Engineering and Management*, *116*(4), 595–608. https://doi.org/10.1061/(asce)0733-9364(1990)116:4(595)

Drew, D., Skitmore, M., & Lo, H. P. (2001). The effect of client and type and size of construction work on a contractor's bidding strategy. *Building and Environment*, *36*(3), 393–406. https://doi.org/10.1016/S0360-1323(00)00009-3

Egemen, M., & Mohamed, A. N. (2007). A framework for contractors to reach strategically correct bid/no bid and mark-up size decisions. *Building and Environment*, *42*(3), 1373–1385. https://doi.org/10.1016/j.buildenv.2005.11.016
Ekström, M., & Björnsson, H. (2000). Automation of AEC Bidding Using Intelligent Agents. *Computing in Civil and Building Engineering (2014)*. https://doi.org/10.1061/40513(279)73
Engelbrecht-Wiggans, R. (1980). *State of the Art—Auctions and Bidding Models: A Survey*. *26*(2), 119–142. https://doi.org/10.1287/mnsc.26.2.119
Friedman, L. (1956). A Competitive-Bidding Strategy. *Operations Research*, *4*(1), 104–112.
Gates, M. (1967). *Bidding Strategies and Probabilities*. https://doi.org/10.1061/JCCEAZ.0000192
Kwasafo, O. K., Laryea, S., & Govender, N. (2025). Using Case Studies to Determine Automatable Activities in Construction Bid Preparation. *CIB Conferences*, *1*(1). https://doi.org/10.7771/3067-4883.1673
Lu, J.-H., Li, S.-Z., Xu, J.-H., Sheng, Z.-B., & Zhang, Q.-M. (2022). Research on the Intelligent Bidding Information Fit Model for Large Enterprises. *2022 International Conference on Engineering Education and Information Technology (EEIT)*, 93–97. https://doi.org/10.1109/EEIT56566.2022.00029
Majeed, M. I. (2025). Ai-Enabled Knowledge And Task Automation: A Framework For Enhancing Employee Adaptive Performance Through Organizational Agility In The Retail Industry. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5281046
Mustafa, M. A., & Ryan, T. C. (1990). Decision support for bid evaluation. *International Journal of Project Management*, *8*(4), 230–235. https://doi.org/10.1016/0263-7863(90)90031-6
Using engineering and construction analytics for better decisions | McKinsey. (n.d.). Www.mckinsey.com. https://www.mckinsey.com/capabilities/operations/our-insights/how-analytics-can-drive-smarter-engineering-and-construction-decisions
Oo, B. L., Lim, T. H. B., & Runeson, G. (2022). Critical Factors Affecting Contractors' Decision to Bid: A Global Perspective. *Buildings*, *12*(3), 379. https://doi.org/10.3390/buildings12030379
Pakgohar, A., Childe, S. J., & Zhang, D. Z. (2013). *A DSS Solution for Integrated Automated Bidding, Subcontractor Selection and Project Scheduling*. https://doi.org/10.1007/978-3-642-41077-2_6
Rothkopf, M. H. (1969). A Model of Rational Competitive Bidding. *Management Science*, *15*(7), 362–373.
Schulte-Althoff, M. (2023). *What's to Automate? A Task Analysis of AI-enabled Start-ups*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2023.201
Shash, A. A. (1998). Subcontractors' Bidding Decisions. *Journal of Construction Engineering and Management*, *124*(2), 101–106. https://doi.org/10.1061/(asce)0733-9364(1998)124:2(101)
Taherdoost, H., & Madanchian, M. (2023). Multi-Criteria Decision Making (MCDM) Methods and Concepts. *Encyclopedia*, *3*(1), 77–87. https://doi.org/10.3390/encyclopedia3010006
Takano, Y., Ishii, N., & Muraki, M. (2014). A sequential competitive bidding strategy considering inaccurate cost estimates. *Omega*, *42*(1), 132–140. https://doi.org/10.1016/j.omega.2013.04.004
vom Brocke, J., Hevner, A., & Maedche, A. (2020). *Introduction to Design Science Research*. https://doi.org/10.1007/978-3-030-46781-4_1
Venable, John R.; Pries-Heje, Jan; and Baskerville, Richard L., "Choosing a Design Science Research Methodology" (2017). *ACIS 2017 Proceedings*. 112. https://aisel.aisnet.org/acis2017/112
Xiao, L., Chen, Z.-S., Zhang, X., Chang, J.-P., Pedrycz, W., & Chin, K.-S. (2020). Bid Evaluation for Major Construction Projects Under Large-Scale Group Decision-Making Environment and Characterized Expertise Levels. *International Journal of Computational Intelligence Systems*, *13*(1), 1227–1242. https://doi.org/10.2991/ijcis.d.200801.002
Zhu, X., Meng, X., & Zhang, M. (2021). Application of multiple criteria decision making methods in construction: A systematic literature review. *Journal of Civil Engineering and Management*, *27*(6), 372–403. https://doi.org/10.3846/jcem.2021.15260