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# Evaluating the Dynamics of Contractors' Tender for Construction Projects: Insights from PCA, Clustering, and Robust Regression

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ABSTRACT

The tendering process is a critical determinant of project success in the construction industry, particularly in Nigeria, where indigenous contractors face numerous challenges in securing government and foreign contracts. This study examines the dynamics influencing contractors' tender decisions by employing Principal Component Analysis (PCA), hierarchical clustering, and robust regression modeling. Data were obtained through structured interviews with experienced professionals, who rated 50 decision-making factors affecting tender submissions. PCA reduced data dimensionality, revealing that a few core components, such as organizational capacity, market conditions, and project risks explain the majority of variance in contractor decisions. Hierarchical clustering identified contractor segmentation based on tender priorities, while robust regression showed a statistically significant relationship between mid-tier factor scores (medium_scores) and overall tender viability. Although limited in scale, the findings offer preliminary insights into predictive, simplified metrics for tender evaluation. This research contributes theoretically by integrating advanced analytical methods into tendering studies and practically by offering actionable insights to contractors, policymakers, and stakeholders aiming to enhance the competitiveness and transparency of the procurement process in Nigeria's construction sector. The study underscores the need for standardized evaluation criteria, capacity-building, and data-driven decision-support systems in tender management.

## Introduction

The construction industry in Nigeria is a cornerstone of national development, offering extensive employment opportunities, infrastructure delivery, and economic stimulation. Yet, despite its significant role, the sector remains fraught with systemic inefficiencies, particularly in the tendering phase of construction project procurement. Designing and implementing an effective tender strategy remains a daunting challenge for many contractors, especially those targeting government contracts. As argued by some authors in the review, cross-country study of West African nations, including Nigeria, many small- and medium-scale contractors are disadvantaged in the tendering process, primarily due to a lack of strategic structuring and consideration of critical decision-making factors. Consequently, these contractors often fail to secure contracts not because they lack capacity, but because they ignore key variables that determine tender success or failure.

Tendering, the process by which construction services are procured, is universally acknowledged as the most critical phase of a construction contract lifecycle [1-2]. It encapsulates a wide array of considerations, from price to experience, risk management, and even stakeholder relationships. In Nigeria, this phase becomes even more complex due to the interplay of public sector dominance, bureaucratic bottlenecks, and limited contractor preparedness [3]. The work by [4] emphasized that tendering is fundamental not only for ensuring transparency in procurement but also for fostering competitiveness and efficiency. Nonetheless, the prevailing approach remains cost-centric—often awarding contracts to the lowest bidder, a practice that has repeatedly been criticized for undermining long-term value and quality [5-6]. International literature and empirical studies indicate that successful tendering requires more than just cost competitiveness. Factors such as contractor capacity, document accuracy, project scope clarity, and alignment with client expectations play a critical role [7-8]. However, in the Nigerian context, particularly in states like Imo, indigenous contractors frequently lack the data-driven insights necessary to optimize their tendering strategies. This is exacerbated by inconsistent tender documentation, compressed preparation timelines, and limited access to critical information [9-

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10]. Although several scholars have examined bidding behaviour and influencing factors, much of the existing research remains descriptive, focusing on isolated variables or theoretical models. The study by [11], for instance, identified 51 potential decision-making factors, categorized into project-related, firm-related, and economic factors.

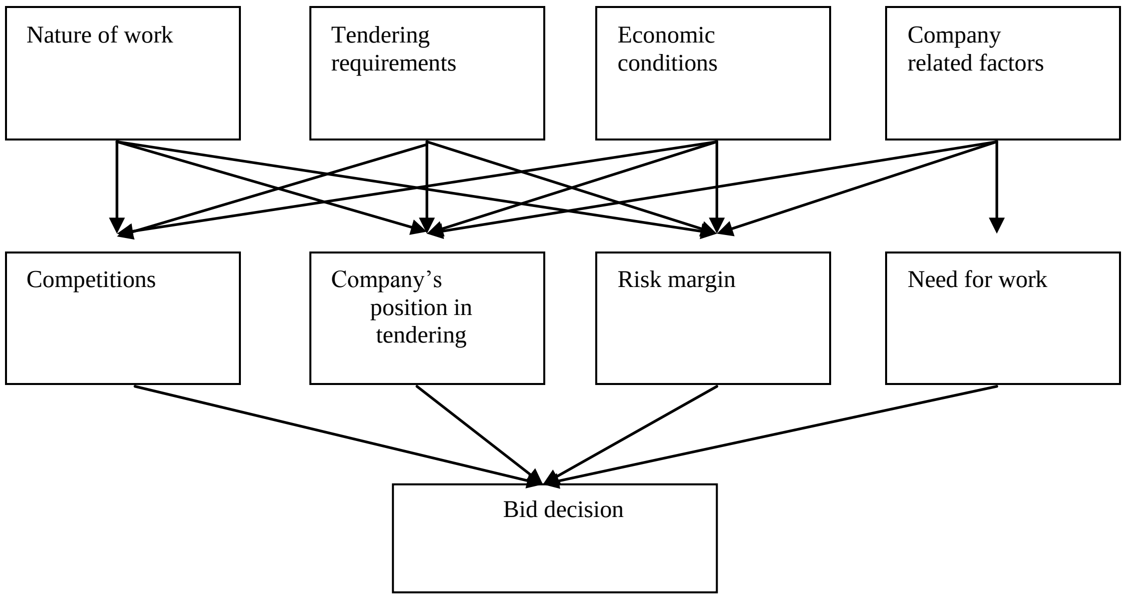


**Fig. 1- Tender reasoning model [11]**

While such studies provide breadth, they often fall short of offering predictive and integrative models that could aid contractors in making informed decisions. Moreover, there is a notable gap in the application of advanced analytical techniques such as Principal Component Analysis (PCA), clustering, and robust regression in unravelling the underlying structure of tendering data and establishing reliable predictors for success or failure. The current study seeks to offer a multidimensional evaluation of tender dynamics using quantitative tools that can distil complexity into actionable insights. PCA will be employed to reduce data dimensionality and highlight the most influential tendering variables. Clustering techniques, including hierarchical clustering and heatmap visualization, will explore latent patterns and groupings among decision factors. Furthermore, robust regression modelling will be used to predict tender decision outcomes based on identified factor scores, offering a more nuanced understanding of what drives success in competitive bidding.

This research is particularly timely given the growing need for indigenous Nigerian contractors to become more competitive in securing public and foreign-funded projects. With over 55% of construction projects financed by the government [3], the inability of local contractors to compete effectively exacerbates economic dependency and stifles domestic capacity development. By providing a data-driven framework, this study aims to support contractors in making smarter bid/no-bid decisions, improving tender document quality, and ultimately enhancing their competitiveness. Furthermore, [12], in their scientometric analysis of construction bidding literature, highlighted the increasing importance of computational techniques in bidding research, noting a shift toward data analytics, predictive modelling, and performance optimization. However, the Nigerian literature remains largely devoid of such approaches, indicating a pressing need for context-specific empirical studies that not only map but also model the decision-making processes of local contractors.

The study by [13], using Hofstede's national culture framework, found that foreign contractors in Zambia outperform local ones in time, cost, and schedule due to better uncertainty management, though locals scored higher in health and safety. The work by [14] emphasized how tender price variability and inflation threaten economic sustainability, identifying 13 key cost-driving factors and proposing strategic responses for sustainable tender pricing. In Egypt, [15] advanced a multi-criteria decision-making model integrating the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR), showing that high-performing contractors may not offer the lowest bid but meet critical performance and safety standards. The work by [16] investigated 148 government tenders and revealed how phenomena such as the wisdom of the crowd, the winner's curse, and cost overruns collectively undermine public project efficiency. Within the Nigerian context, [17] identified factors such as project complexity, political influence, and document clarity as key to contractor success. Also, the study by [18] emphasized the role of contractor selection criteria such as managerial competence and financial strength in achieving timely and cost-effective project delivery. Similarly, [19] highlighted flaws in Nigeria's tendering system, including political interference and weak contractor capacity, recommending procedural reforms and improved coordination to enhance delivery outcomes.

Hence, this study offers both theoretical and practical contributions. Theoretically, it integrates advanced quantitative methods with construction tendering literature to uncover hidden relationships among critical decision-making factors. Practically, it provides evidence-based recommendations for contractors, policymakers, and stakeholders seeking to improve tendering outcomes and foster inclusive growth within Nigeria's construction sector. The aim of this study is to evaluate the underlying structure and predictive relationships among key decision-making factors in tendering processes using Principal Component Analysis (PCA), clustering techniques, and robust regression modeling. The goal is to simplify complex multivariate data, identify critical groupings, and establish reliable predictors that influence tender evaluation outcomes. The Objectives of the Study are: To apply Principal Component Analysis (PCA) to reduce the dimensionality of tender-related factors and identify the most significant components that explain the majority of the variance in the data; To utilize clustering techniques (hierarchical clustering and heatmap analysis) to explore patterns and similarities among participant responses and decision-making factors in tender evaluation; To assess the relative importance of key factors by visualizing their ratings and identifying high- and low-priority attributes using descriptive plots such as boxplots and mean ranking charts; To develop a robust regression model for evaluating the predictive relationship between medium-level factor scores and overall tender decision scores, including statistical validation of coefficients and residual analysis; and To provide practical insights that support more efficient, data-driven bid/no-bid decisions by identifying core themes and reliable predictors in tender assessments.

**1.1 Conceptual Framework**

A conceptual model (Fig. 2) was developed to guide the study, linking 50 factors categorized into firm-related, project-related, and economic variables with analytical techniques (PCA, clustering, and regression) to predict tender outcomes.

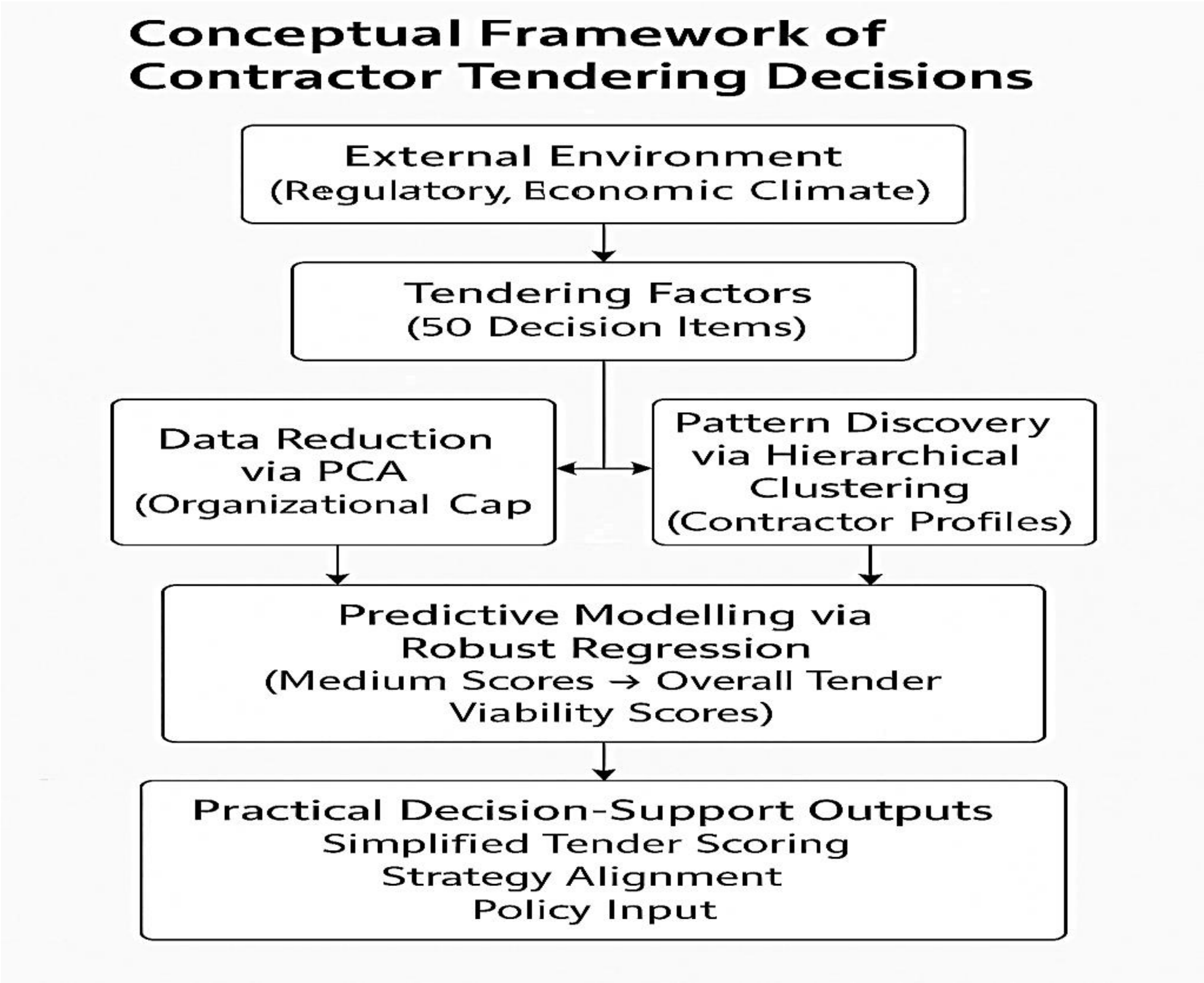


**Fig. 2- Conceptual Framework of Contractor Tendering Decisions**

## 2 Material and Methods

### 2.1 Participants and Data Collection

Data for this study were collected through a face-to-face structured interview format that incorporated a standardized questionnaire as the main data collection instrument. This approach was chosen to ensure consistency in responses and to allow the researcher to probe for deeper insights when necessary. The questionnaire guided the structure of the interviews, with most of the questions delivered in a closed-ended format to facilitate ease of analysis, while selected open-ended components enabled more detailed, qualitative feedback. Before the interviews, 12 potential participants were contacted and provided with a participant information sheet and consent form to ensure informed participation. Out of the 12, only 10 agreed to participate, and following a screening process based on experience in the construction industry, 8 participants were deemed eligible and included in the final sample, resulting in a 67% response rate. Each interview lasted approximately 30 minutes and was conducted in a comfortable and distraction-free environment to encourage open communication. The interview process was divided into three sections: first, demographic and background information was collected using multiple-choice questions; second, participants rated 50 validated decision-making variables derived from [20] and revised through expert consultation. The sample, while small, represents an exploratory phase to guide future large-scale research. Care was taken to ensure neutrality during the interview to avoid introducing bias, and all responses were recorded systematically for subsequent analysis. This method provided a balance between quantitative measurement and qualitative depth, aligning with the research objectives and constraints.

### 2.2. Variable Construction and Validation

The 50 variables used were adapted from established models [20], reviewed by three industry experts, and categorized into firm, project, and economic-related domains. Validation involved pre-testing with two construction professionals and iterative refinement.

### 2.3. Method of data analysis

The data analysis for this study involved a mixed-methods approach, combining both quantitative and qualitative techniques to provide comprehensive insights into the tender decision-making process. Quantitative data collected through structured questionnaires were analyzed using Principal Component Analysis (PCA), hierarchical clustering, heatmaps, and robust regression techniques. PCA was employed to reduce the dimensionality of the dataset and identify underlying patterns among the 50 decision-making factors [21]. As recommended by [22], PCA is a widely accepted technique for summarizing the variance within a large set of interrelated variables, allowing the extraction of key components that retain most of the original information. In this study, the first three principal components explained approximately 59.2% of the total variance, justifying a dimensionality reduction to three to five components without substantial loss of information. The scree plot confirmed the steep decline in variance contribution after the fourth component, supporting the selection of key components for interpretive focus.

Following PCA, a biplot was generated to visualize the variable contributions to the first two components and to identify correlations among factors and clustering of participant responses. This helped to reveal the structure of relationships in the data, particularly highlighting key variables with strong influence across participants. Hierarchical clustering was then applied to both the participants and the rating factors to uncover patterns of similarity and groupings. The dendrogram and cluster heatmap effectively illustrated how participants with similar decision-making priorities could be categorized, a technique consistent with best practices in exploratory data analysis as outlined by [23].

In addition to dimensionality reduction and clustering, robust regression analysis was conducted to examine the predictive relationship between medium scores (aggregated mid-level ratings) and overall_scores (general evaluation of tender viability). Medium_scores refers to the mean of factors ranked within the interquartile range (25th–75th percentile) of importance by respondents, representing mid-level influences in tender decisions. Robust regression was chosen due to its resilience to outliers and heteroscedasticity, ensuring stable parameter estimates in small samples [24].

Complementary visualizations, such as heatmaps and boxplots, were used to further explore rating distributions and inter-variable relationships. The heatmaps highlighted variability in factor importance among participants, revealing areas of consensus and divergence. Boxplots compared the dispersion of ratings in the overall and medium score categories, while the correlation heatmap confirmed a strong positive association between them suggesting that medium_scores could serve as a reliable proxy for overall evaluation in future models.

Through the integration of PCA, clustering, robust regression, and visualization tools, this analysis provides a rigorous and multi-layered understanding of the tender decision-making landscape. This methodological combination enhances interpretability, reduces noise in the data, and aligns with contemporary best practices in construction management research [25-26].

## 3. Result and Discussion

This section presents the application of Principal Component Analysis (PCA) to uncover latent structures in the decision-making dataset. By reducing dimensionality while preserving the most critical variance, PCA facilitates the interpretation of complex patterns and relationships among variables.

**Table 1-Summary result of the Principal Component Analysis**

| Component | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|---|---|---|---|---|---|---|---|---|
| **Standard Deviation** | 1.3208 | 1.3039 | 1.1372 | 0.986 | 0.9094 | 0.83444 | 0.65023 | 0.58626 |
| **Proportion of Variance** | 0.2181 | 0.2125 | 0.1617 | 0.1215 | 0.1034 | 0.08704 | 0.05285 | 0.04296 |
| **Cumulative Proportion** | 0.2181 | 0.4306 | 0.5923 | 0.7138 | 0.8172 | 0.90419 | 0.95704 | 1 |

The results from Table 1 indicate that the first three principal components (PCs) capture a substantial amount of the variance in the dataset. Specifically, PC1 explains 21.8%, PC2 explains 21.3%, and PC3 explains 16.2% of the total variance, collectively accounting for approximately 59.2% of the information contained in the original variables. Extending to PC5 covers over 81.7%, suggesting that a reduced dimensionality of about 3 to 5 components is sufficient to summarize the core structure of the data. This reduction can simplify analysis and visualization without losing much information. The implication for decision-making is that complex, multi-factor tendering decisions can potentially be grouped into a few core themes (e.g., firm capacity, market conditions, project risk), which can streamline assessments and improve the efficiency of bid/no-bid decisions.

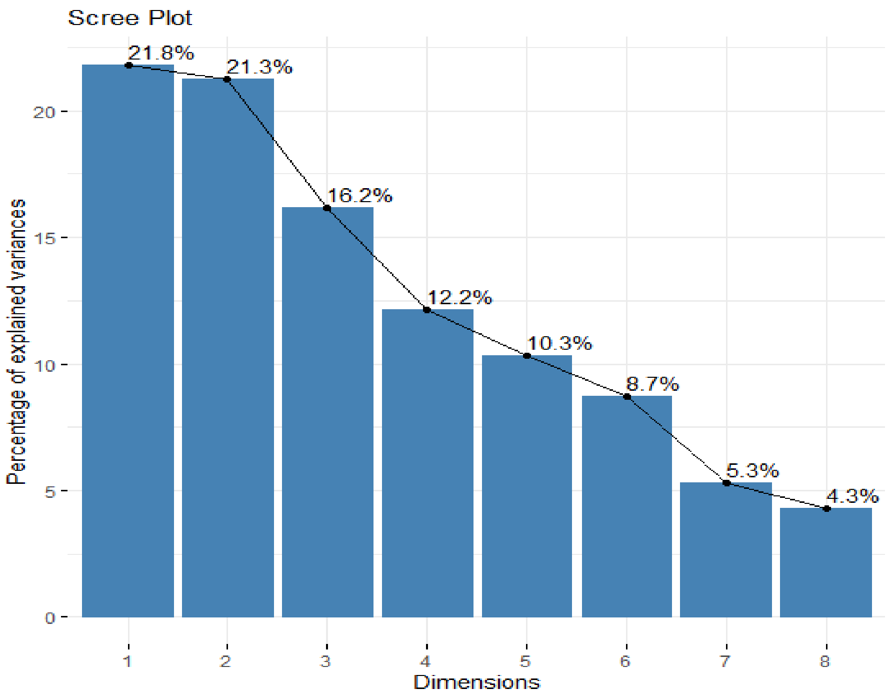


**Fig. 3- Scree plot to visualize explained variance**

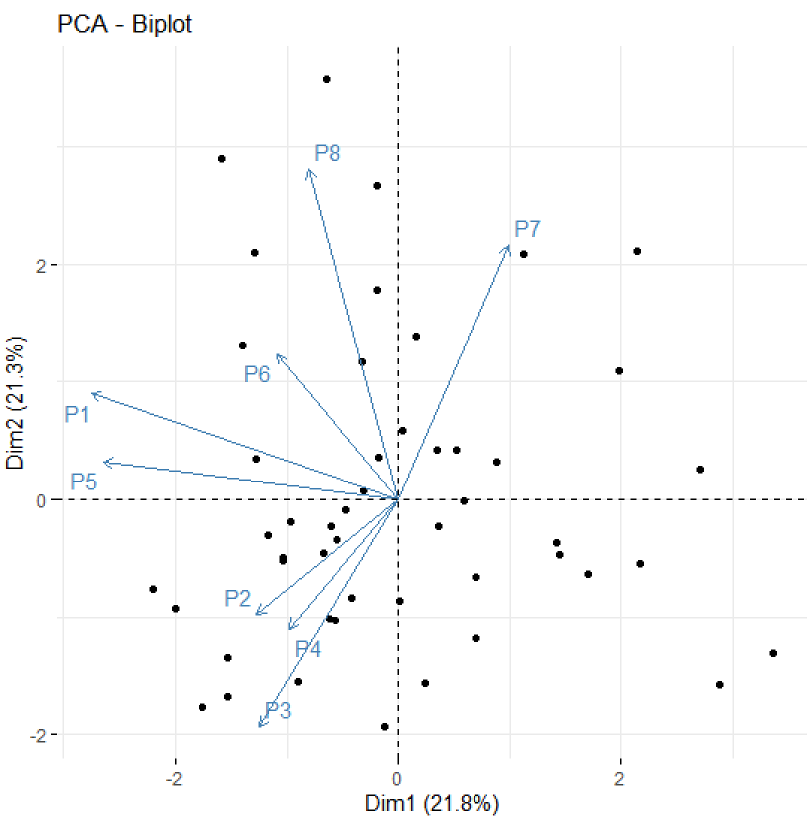


**Fig. 4- PCA Biplot of the responses**

Fig. 3 is a scree plot that illustrates the percentage of explained variance for each principal component (dimension) in a dataset. The plot shows a clear decline in explained variance as the number of dimensions increases. The first two dimensions account for the highest proportion of variance, explaining 21.8% and 21.3% respectively, totaling 43.1%. The third and fourth components explain 16.2% and 12.2% respectively, bringing the cumulative total to approximately 71.5%. After the fourth dimension, the additional components contribute progressively less to the explained variance. This suggests that the first four dimensions capture the majority of the information in the dataset, and may be sufficient for dimensionality reduction or further analysis without significant loss of information.

Fig. 4 presents a PCA biplot that visualizes the relationship between the original variables (P1–P8) and the first two principal components (Dim1 and Dim2), which together explain 43.1% of the total variance in the dataset (21.8% from Dim1 and 21.3% from Dim2). Each arrow represents a variable, with the direction and length indicating its contribution to the principal components. Variables such as P1, P5, and P7 have longer arrows, indicating stronger contributions to the components, while the angles between the arrows reflect the correlations between variables (smaller angles imply stronger positive correlations). The scatter of black dots represents individual observations projected in the reduced two-dimensional space. The plot suggests that most of the variation in the data can be interpreted by observing how strongly each variable aligns with Dim1 and Dim2, helping to identify clusters, patterns, or potential outliers in the responses.

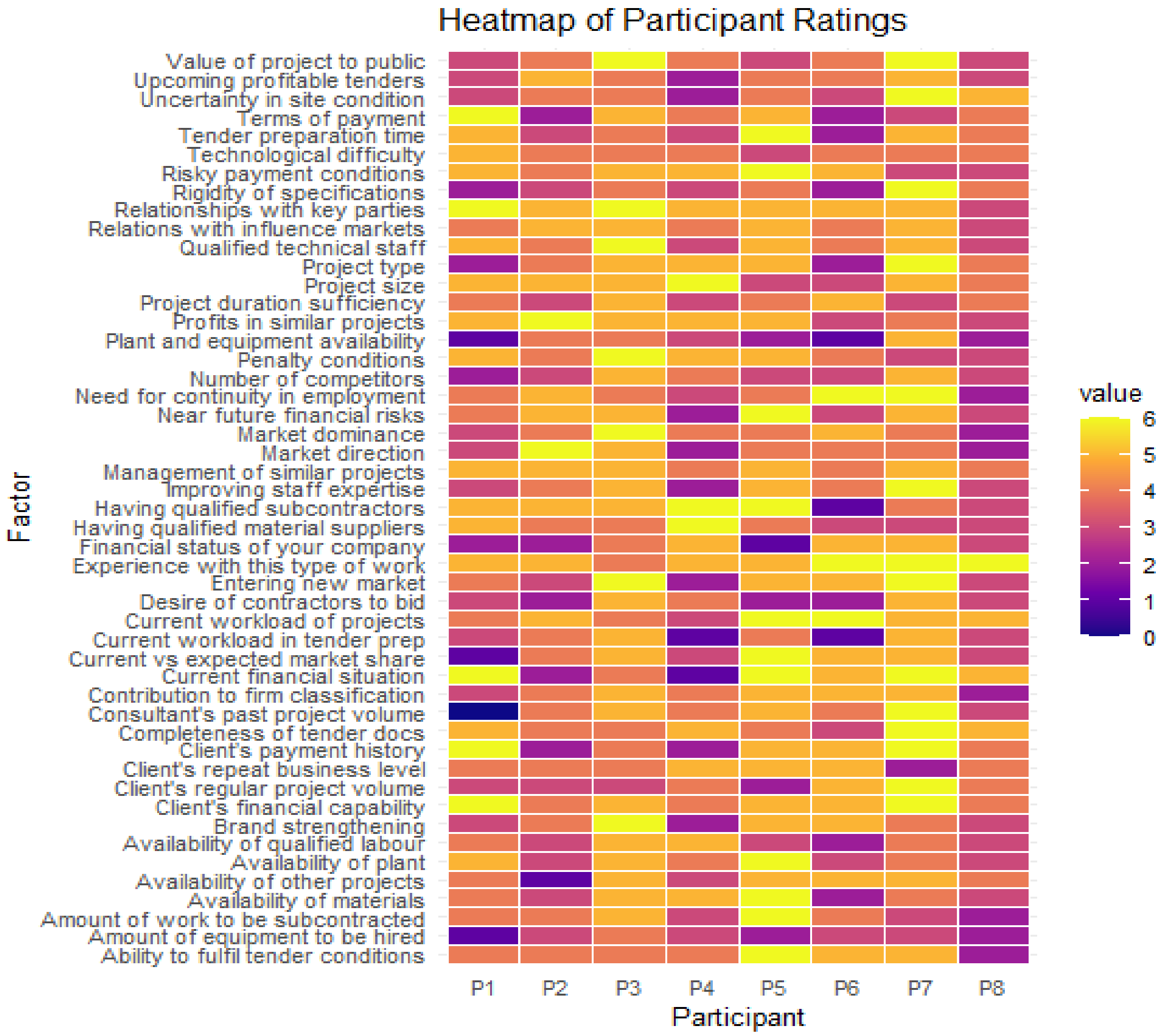


**Fig. 5= Heatmap of Participants Ratings**

Fig. 5 presents a heatmap showing the ratings of various decision-making factors by participants P1 through P8. The colour gradient, ranging from dark purple (low rating) to bright yellow (high rating), illustrates the degree of importance or influence each participant assigned to each factor. The heatmap reveals variation in perception across participants, with certain factors; such as "Current financial situation," "Current vs expected market share," "Availability of materials," and "Ability to fulfil tender conditions" frequently receiving higher ratings (yellow shades), indicating they are generally considered crucial. In contrast, factors like "Consultant’s past project volume" and "Brand strengthening" show lower or more inconsistent ratings (darker shades), implying less perceived significance. In summary, the heatmap highlights both consensus and divergence among participants, providing insights into key drivers and differing priorities in tender-related decision-making.

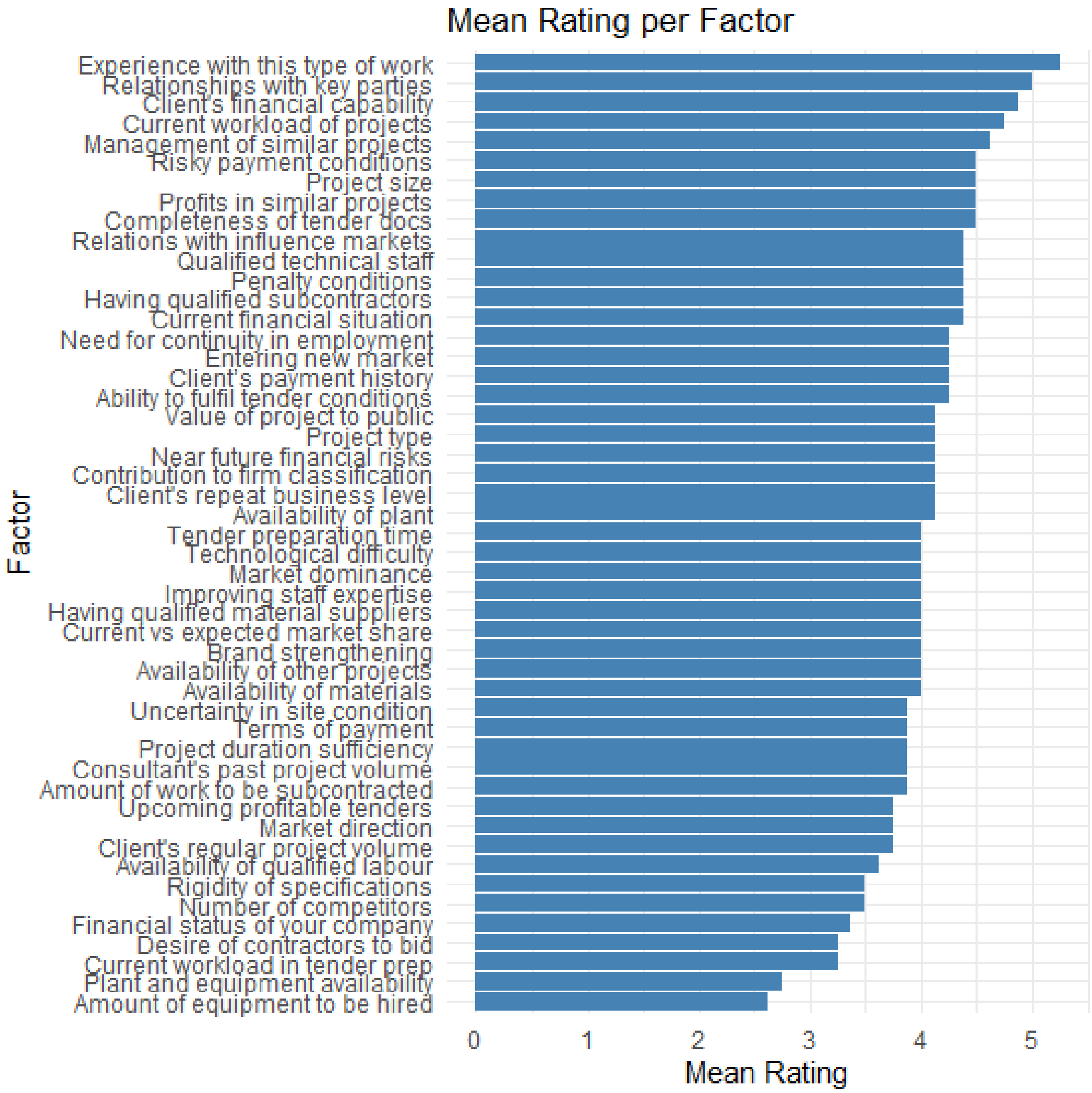


**Fig. 6- Mean Rating per Factor of the Participants**

Fig. 6 displays the mean rating per factor across all participants, providing a clear ranking of the most and least influential factors in tender-related decision-making. The top-rated factor, “Experience with this type of work,” received the highest average rating, underscoring its critical role in decision-making. This is closely followed by “Relationships with key parties,” “Client’s financial capability,” and “Current workload of projects,” reflecting the importance of both practical experience and financial and relational stability. On the other end, factors like “Amount of equipment to be hired,” “Plant and equipment availability,” and “Current workload in tender prep” received the lowest mean ratings, suggesting they are considered less pivotal in influencing decisions. Overall, the implications point to a strong emphasis on proven competence, strategic relationships, and financial credibility as the most influential drivers for successful project bidding, while logistical and preparatory elements are seen as relatively secondary.

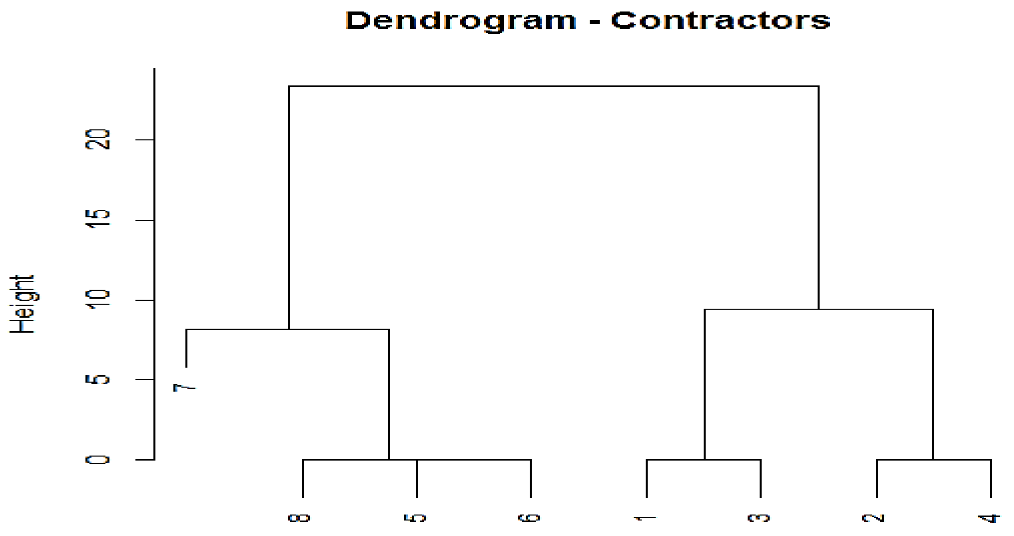


**Fig. 7- Hierarchical clustering for participants**

Fig. 7 shows a hierarchical clustering dendrogram for participants. Two main clusters emerge: one includes participants 5, 6, 7, and 8; the other includes 1, 2, 3, and 4. The height axis indicates dissimilarity, with the final merge occurring above 20, showing substantial difference between the two primary groups.

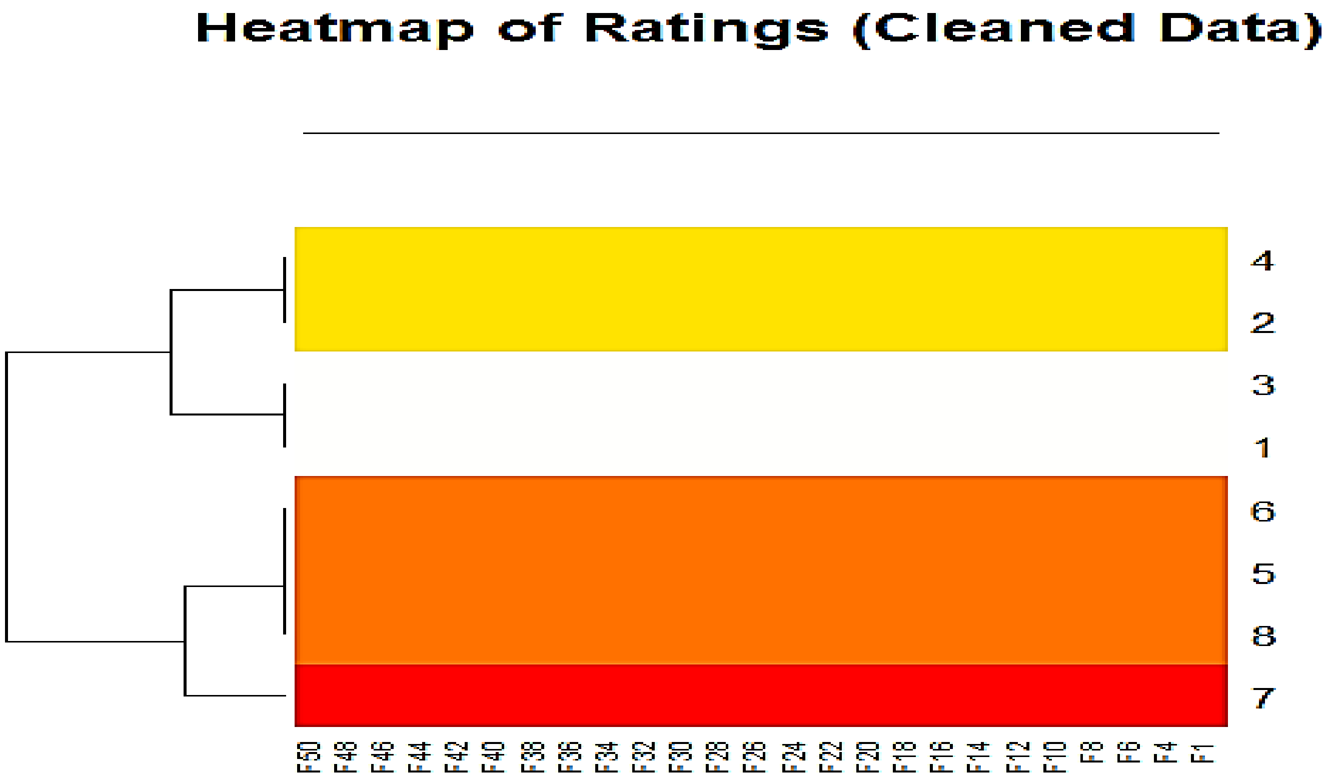


**Fig. 8-Plot of heatmap with correct dendrograms**

Fig. 8 presents a heatmap of cleaned ratings data, accompanied by dendrograms that depict hierarchical clustering among the features (labeled F1 through F50). The clustering along both axes suggests patterns of similarity among the data points, with distinct color bands (yellow, orange, and red) indicating different intensity levels of ratings. The heatmap reveals three main clusters of features that share similar rating patterns, implying that certain groups of features are rated similarly by respondents. For instance, features F1 to F30 fall into a high-rating cluster (red), suggesting they are consistently perceived more favorably. Meanwhile, features F31 to F50 exhibit lower ratings (yellow and orange), indicating less favorable responses. This clustering can guide targeted interventions or prioritizations—such as enhancing lower-rated features or maintaining the strengths of those with high ratings.

**Result of the Robust Regression Analysis**

The residuals are the differences between the observed and predicted values of overall_scores.

**Table 2-Summary result of Residuals**

| Min | 1st Quartile (Q1) | Median | 3rd Quartile (Q3) | Max |
|---|---|---|---|---|
| **-0.0732** | -0.0118 | 0.0056 | 0.0157 | 0.0281 |

The residuals in Table 2 indicate a relatively small range, meaning that the model's predictions are close to the observed values. The median residual is close to zero, indicating that the model fits well on average. The residuals indicate a relatively small range, meaning that the model's predictions are close to the observed values.

**Table 3-Result of Coefficients**

| Predictor | Estimate | Std. Error | t-value |
|---|---|---|---|
| **Intercept** | 0.431 | 0.0442 | 9.7583 |
| **medium_scores** | 0.3744 | 0.0664 | 5.6404 |

The coefficients represent the effect of the predictors (in this case, medium_scores) on the dependent variable (overall_scores).

The result presented in Table 3 found that the intercept is 0.4310, which means when medium_scores is zero, the expected value of overall_scores is 0.4310. The coefficient for medium_scores is 0.3744. This indicates that for each one-unit increase in medium_scores, the overall_scores increase by 0.3744 units. The t-values for both the intercept and the medium_scores coefficient are significant (9.7583 for the intercept and 5.6404 for medium_scores), suggesting that both are significantly different from zero and have a meaningful impact on the model.

The findings showed that when medium_scores are zero, the overall_scores are expected to be 0.4310. This is the baseline score for overall_scores when no influence from the medium_scores is considered. Also, for every 1-unit increase in medium_scores, overall_scores increase by 0.3744 units. This shows a positive relationship between the two variables, suggesting that higher medium_scores tend to lead to higher overall_scores. Both the intercept and the slope (coefficient of medium_scores) have high t-values (greater than 2), indicating that the results are statistically significant. Therefore, the model suggests a meaningful relationship between medium_scores and overall_scores. The residuals indicate that the model fits the data well, with no major discrepancies between observed and predicted values. Hence, the robust regression model suggests that medium_scores is a significant predictor of overall_scores, with a positive relationship.

Figure 9 shows a boxplot comparison between two rating categories: overall_score and medium_score. The plot reveals that medium_score has a slightly higher median and a more compact interquartile range (IQR), indicating more consistent ratings among respondents. In contrast, overall_score exhibits a wider spread, suggesting greater variability in how participants rated this category. The presence of a larger spread in overall_score could imply differing interpretations or experiences contributing to the score, whereas medium_score appears to be more uniformly evaluated. These findings suggest that medium_score may serve as a more stable metric for assessing quality or satisfaction, while overall_score might benefit from further clarification or segmentation to better understand the sources of variation.

Fig. 10 presents a correlation heatmap illustrating the relationship between overall_score and medium_score. The strong red colour in the intersecting cells, aligned with the scale approaching 1, indicates a very high positive correlation between the two variables. This suggests that as medium_score increases, overall_score tends to increase proportionally, and vice versa. The high correlation implies that medium_score could be a reliable predictor or proxy for overall_score, potentially reducing redundancy in future analyses or simplifying rating systems. Additionally, this close relationship validates the consistency between general impressions (overall score) and more specific or aggregated evaluations (medium score), supporting the integrity and coherence of the scoring system used.

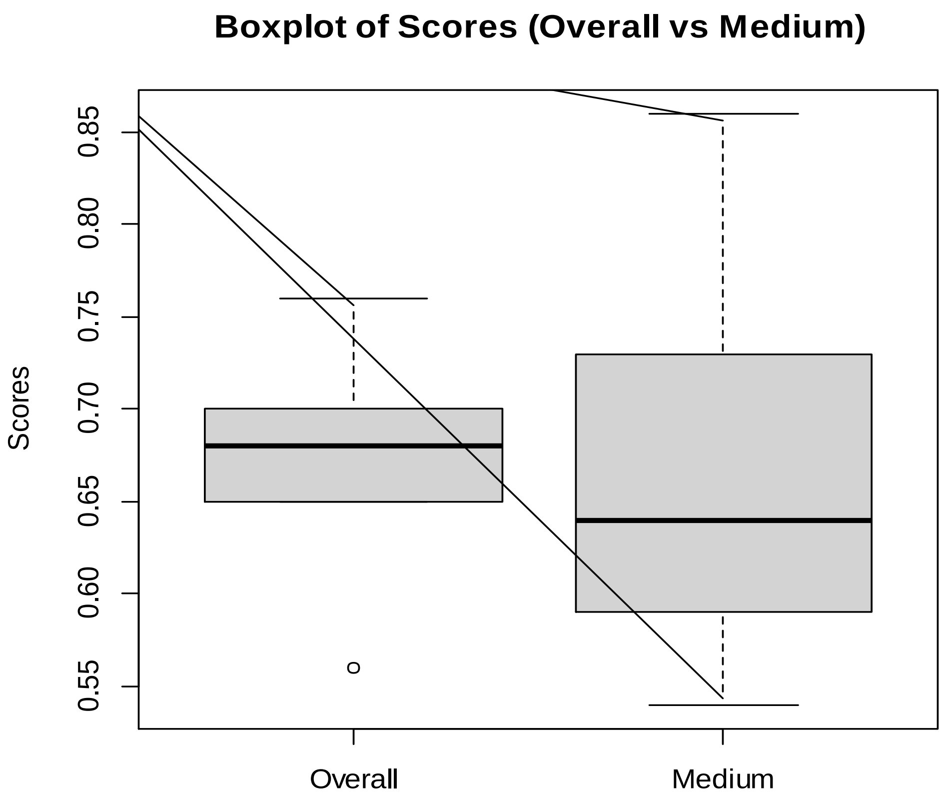


**Fig. 9- Boxplot Comparison of Ratings between Overall_score and Medium_score**

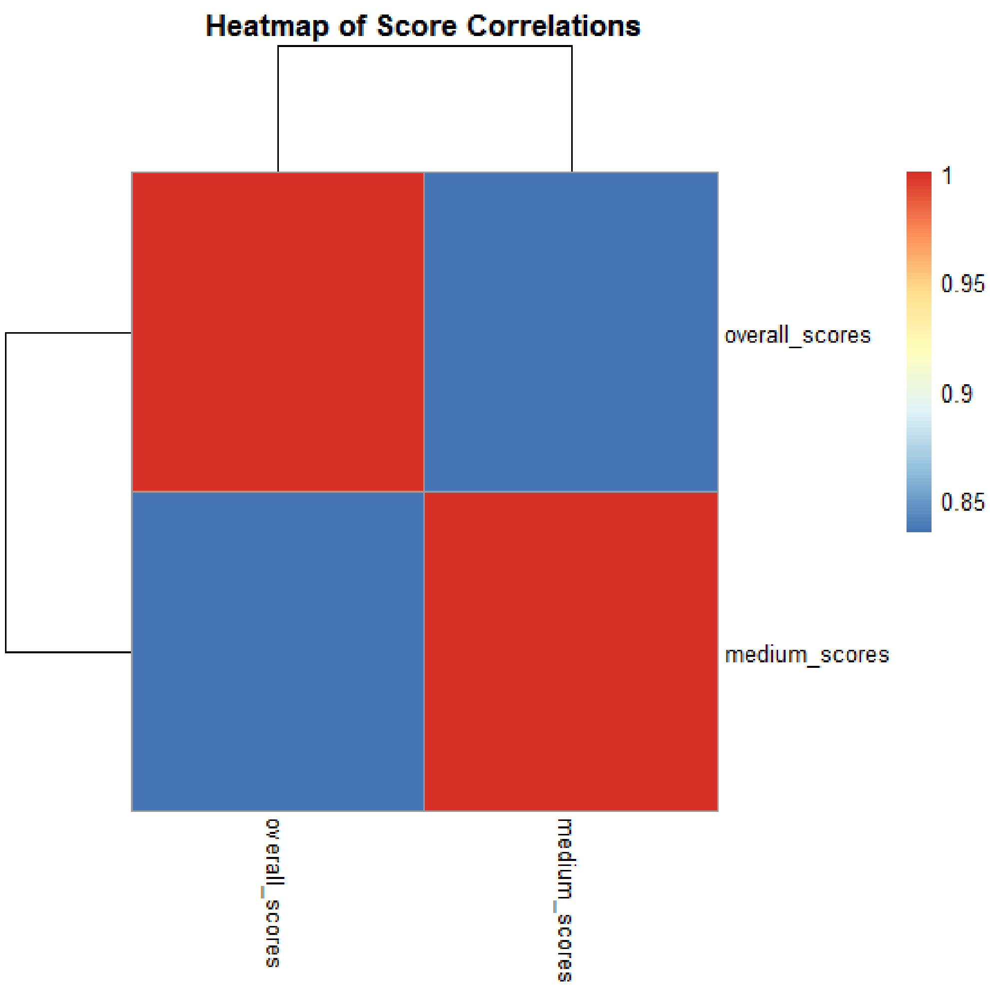


**Fig. 10-Correlation Heatmap of Ratings between Overall_score and Medium_score**

**4. Conclusion**

This study presents a novel, data-driven approach to understanding contractors' tender evaluation behaviour in the Nigerian construction sector. Conceptually, it integrates Principal Component Analysis (PCA), hierarchical clustering, and robust regression into construction management literature. Practically, it introduces medium_scores a statistically significant and predictive proxy for tender viability that simplifies complex evaluation frameworks without compromising rigour.

The PCA findings reveal that three to five components explain up to 81.7% of the variance in decision-making, distilling complex factors into themes such as organizational capacity, market conditions, and project-related risks. This aligns with the findings of [17-19], who emphasized decision factors like documentation clarity, project complexity, and contractor competence. It contrasts, however, with cost-centric models that still dominate practice, as noted by [13; 15].

Clustering analysis further reveals distinctive decision-making profiles among contractors, suggesting tailored interventions and segmented capacity-building efforts. The robust regression model confirms medium_scores as a reliable predictor of overall_scores, supported by heatmap and boxplot visualizations. This echoes the call by [16] for more accurate bid evaluations to counter the "winner's curse" and cost overruns.

Despite the study's limited sample size, its methodological robustness and findings provide a strong basis for future research. Thus, the implications are as follows:

i. Simplifying evaluation using statistically validated dimensions reduces subjectivity and enhances transparency.

ii. Segmentation of contractor behaviour via clustering enables targeted capacity development and strategic alignment.

iii. The use of PCA and regression can transform tender evaluation into a more empirical, reliable process.

This work contributes to addressing inefficiencies highlighted in previous studies and paves the way for smarter, evidence-based procurement practices. Future research should scale the model across regions and project types, apply longitudinal designs, and integrate outcome-based validation to further test and refine the framework.

Based on the outcome of this study, the following recommendations were suggested:

i. Regulators and industry bodies should adopt simplified, data-driven prequalification systems grounded in identified core dimensions.
ii. Firms should integrate clustering and PCA-based decision-support tools to improve strategic tendering.
iii. Training programs must focus on boosting contractor capabilities in market risk analysis, financial planning, and relationship management.
iv. Broader datasets and longitudinal research are needed to test generalizability and link decision variables to project performance outcomes.

In conclusion, this study bridges the gap between statistical rigor and practical utility in the evaluation of tendering decisions, offering a replicable framework for enhancing efficiency, transparency, and competitiveness in construction procurement.

## Acknowledgement

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**Appendix A: Raw data**

| Factors | participants | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| **Need for work** | | | | | | | | |
| 1. Current workload of projects, relative to the capacity of your firm | 4 | 5 | 4 | 3 | 6 | 6 | 5 | 5 |
| 2. Availability (number and size) of other projects within the market | 4 | 1 | 5 | 3 | 5 | 5 | 5 | 4 |
| 3. Current financial situation of the company | 6 | 2 | 4 | 1 | 6 | 5 | 6 | 5 |
| 4. Need for continuity in employment of key personnel and workforce | 4 | 5 | 4 | 3 | 4 | 6 | 6 | 2 |
| 5. Current workload in tender preparation | 3 | 4 | 5 | 1 | 4 | 1 | 5 | 3 |
| **Strength of firm** | | | | | | | | |
| 6. Ability to fulfil tender conditions imposed by the client | 4 | 4 | 4 | 4 | 6 | 5 | 5 | 2 |
| 7. Financial status of your company (working cash requirement of project) | 2 | 2 | 4 | 5 | 1 | 5 | 5 | 3 |
| 8. Experience and familiarity of your firm with this specific type of work | 5 | 5 | 4 | 5 | 5 | 6 | 6 | 6 |
| 9. Possessing enough qualified technical staff to do the job | 5 | 4 | 6 | 3 | 5 | 4 | 5 | 3 |
| 10. Possessing enough required plant and equipment to do the job | 1 | 4 | 4 | 3 | 2 | 1 | 5 | 2 |
| 11. Having qualified subcontractors | 5 | 5 | 5 | 6 | 6 | 1 | 4 | 3 |
| 12. Having qualified material suppliers | 5 | 4 | 4 | 6 | 4 | 3 | 3 | 3 |
| 13. Amount of work to be subcontracted relative to the total volume of work | 4 | 4 | 5 | 3 | 6 | 4 | 3 | 2 |
| 14. Amount of equipment that needs to be hired and the hire rates in the market | 1 | 3 | 4 | 3 | 2 | 3 | 3 | 2 |
| **Project conditions contributing to profitability of the project** | | | | | | | | |
| 15. Project size (total tender value) | 5 | 5 | 5 | 6 | 3 | 3 | 5 | 4 |
| 16. Terms of payment | 6 | 2 | 5 | 4 | 5 | 2 | 3 | 4 |
| 17. Project type | 2 | 4 | 5 | 5 | 5 | 2 | 6 | 4 |
| 18. Profits made in similar projects in the past | 5 | 6 | 5 | 5 | 5 | 3 | 4 | 3 |
| **Job uncertainty** | | | | | | | | |
| 19. Uncertainty related to the construction site condition | 3 | 4 | 4 | 2 | 4 | 3 | 6 | 5 |
| 20. Completeness of the tender documents (drawings, specifications, etc.) | 5 | 4 | 4 | 5 | 4 | 3 | 6 | 5 |
| **Job complexity** | | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 21. Technological difficulty of the project being beyond the capability of the firm | 5 | 4 | 4 | 4 | 3 | 4 | 4 | 4 |
| 22. Management of similar size projects in the past | 5 | 5 | 5 | 4 | 5 | 4 | 5 | 4 |
| **Risk creating job and contract conditions** | | | | | | | | |
| 23. Rigidity of specifications | 2 | 3 | 4 | 3 | 4 | 2 | 6 | 4 |
| 24. Allowed project duration being enough | 4 | 3 | 5 | 3 | 4 | 5 | 3 | 4 |
| 25. Penalty conditions for not being able to complete the project on time | 5 | 4 | 6 | 5 | 5 | 4 | 3 | 3 |
| 26. Payment conditions of the project creating a risky environment | 5 | 4 | 5 | 5 | 6 | 5 | 3 | 3 |
| 27. Allowed duration for tender preparation being enough | 5 | 3 | 4 | 3 | 6 | 2 | 5 | 4 |
| **Client and consultant of the project** | | | | | | | | |
| 28. Current financial capability of the client | 6 | 4 | 5 | 4 | 5 | 5 | 6 | 4 |
| 29. History of client"s payments in past projects (considering delays, shortages) | 6 | 2 | 4 | 2 | 5 | 5 | 6 | 4 |
| **Factors** | **participants** | | | | | | | |
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| **Availability of resources within the region** | | | | | | | | |
| 30. Availability of required qualified labour within the region | 4 | 3 | 5 | 5 | 3 | 2 | 4 | 3 |
| 31. Availability of the required materials within the region | 4 | 3 | 5 | 5 | 6 | 2 | 4 | 3 |
| 32. Availability of the required plant within the region | 5 | 3 | 5 | 4 | 6 | 3 | 4 | 3 |
| **Competition (considering only the current project)** | | | | | | | | |
| 33. Possible number of competitors passing the requirements | 2 | 3 | 5 | 4 | 3 | 3 | 5 | 3 |
| 34. Desire of qualified contractors to tender and win the project | 3 | 2 | 5 | 4 | 2 | 2 | 5 | 3 |
| **Foreseeable future market conditions & firm's financial situation** | | | | | | | | |
| 35. Market"s direction (whether it is declining, expanding, etc.) | 3 | 6 | 5 | 2 | 4 | 4 | 4 | 2 |
| 36. Amount of possible upcoming profitable projects out for tender in near future | 3 | 5 | 4 | 2 | 4 | 4 | 5 | 3 |
| 37. Existing financial conditions indicating a financial risk in near future | 4 | 5 | 5 | 2 | 6 | 3 | 5 | 3 |
| 38. Ratio of your firm"s current market share to the expected or aimed share | 1 | 4 | 5 | 3 | 6 | 5 | 5 | 3 |
| **Client (considering long-term gains/losses)** | | | | | | | | |
| 39. Amount of work the client carries out regularly | 3 | 3 | 3 | 4 | 2 | 5 | 6 | 4 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 40. Amount of repeat business level that the client been following | 4 | 4 | 4 | 5 | 5 | 5 | 2 | 4 |
| **Project (considering long-term gains and losses)** | | | | | | | | |
| 41. Possible contribution to increase the contractor firm‟s classification | 3 | 4 | 5 | 4 | 5 | 5 | 5 | 2 |
| 42. Possible contribution to increase the firm‟s identity and brand strength | 3 | 4 | 6 | 2 | 5 | 5 | 4 | 3 |
| 43. Possible contribution in increasing firm‟s market share and dominance in market | 3 | 4 | 6 | 4 | 4 | 5 | 4 | 2 |
| 44. Possible contribution in building long-term relationships with other key parties | 6 | 5 | 6 | 5 | 5 | 5 | 5 | 3 |
| 45. Contribution in maintaining long-term relations with important influence markets | 4 | 5 | 5 | 4 | 5 | 4 | 5 | 3 |
| 46. Possible contribution in improving your firm‟s staff expertise | 3 | 4 | 5 | 2 | 5 | 4 | 6 | 3 |
| 47. Possible contribution to break into a new market with productive future | 4 | 3 | 6 | 2 | 5 | 5 | 6 | 3 |
| 48. Contribution to firm‟s future due to value of the completed project to the public | 3 | 4 | 6 | 4 | 3 | 4 | 6 | 3 |
| **Consultant firm (considering long-term gains and losses)** | | | | | | | | |
| 49. Amount of construction work the consultant has been carrying out regularly | 0 | 4 | 5 | 4 | 5 | 4 | 6 | 3 |

**Appendix B: Questionnaire**
**Questionnaire: Factors affecting the tender/ no tender decision making process of two contractors in Lagos**

**Part 1: Company information (please tick one)**

| 1. How many full time employees does your company have? |
|---|
| o 0-5 o<br>6-9 o<br>10-19 |

| 2. What is the main type of projects that your company constructs? |
|---|

Residential o Commercial

Others (please state)

3. How many years have you worked in the construction industry?

o 0-9 o
10-19 o
20-29 o
30+

4. What is the percentage of jobs obtained through competitive tendering?

o 0%-25% º
26%-50% º
51%-75% º
76%-100%

5. What is the percentage of rejected tender invitations?

o 0%-25% º
26%-50% º
51%-75% º
76%-100%

6. What is your job role?

o Estimator o
Commercial manager
o Project manager o
Others (please state)

**Part 2: Factors affecting the tender/ no tender decision making process**

How important do you think the following factors are in affecting the tender/ no tender decision making process for your company? (Please rate the factors by using 0 to 6 score. 0: not important at all; 6: very important.

| Factors | Levels of importance least → most | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| **Need for work** | | | | | | | |
| 1. Current workload of projects, relative to the capacity of your firm | | | | | | | |
| 2. Availability (number and size) of other projects within the market | | | | | | | |
| 3. Current financial situation of the company | | | | | | | |
| 4. Need for continuity in employment of key personnel and workforce | | | | | | | |
| 5. Current workload in tender preparation | | | | | | | |
| **Strength of firm** | | | | | | | |
| 6. Ability to fulfil tender conditions imposed by the client | | | | | | | |
| 7. Financial status of your company (working cash requirement of project) | | | | | | | |
| 8. Experience and familiarity of your firm with this specific type of work | | | | | | | |
| 9. Possessing enough qualified technical staff to do the job | | | | | | | |
| 10. Possessing enough required plant and equipment to do the job | | | | | | | |
| 11. Having qualified subcontractors | | | | | | | |
| 12. Having qualified material suppliers | | | | | | | |
| 13. Amount of work to be subcontracted relative to the total volume of work | | | | | | | |
| 14. Amount of equipment that needs to be hired and the hire rates in the market | | | | | | | |

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| **Project conditions contributing to profitability of the project** | | | | | | | |
| 15. Project size (total tender value) | | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 16. Terms of payment | | | | | | | |
| 17. Project type | | | | | | | |
| 18. Profits made in similar projects in the past | | | | | | | |
| **Job uncertainty** | | | | | | | |
| 19. Uncertainty related to the construction site condition | | | | | | | |
| 20. Completeness of the tender documents (drawings, specifications, etc.) | | | | | | | |
| **Job complexity** | | | | | | | |
| 21. Technological difficulty of the project being beyond the capability of the firm | | | | | | | |
| 22. Management of similar size projects in the past | | | | | | | |
| **Risk creating job and contract conditions** | | | | | | | |
| 23. Rigidity of specifications | | | | | | | |
| 24. Allowed project duration being enough | | | | | | | |
| 25. Penalty conditions for not being able to complete the project on time | | | | | | | |
| 26. Payment conditions of the project creating a risky environment | | | | | | | |
| 27. Allowed duration for tender preparation being enough | | | | | | | |
| **Client and consultant of the project** | | | | | | | |
| 28. Current financial capability of the client | | | | | | | |
| 29. History of client's payments in past projects (considering delays, shortages) | | | | | | | |
| 30. Client's attitude, characteristics and stability in needs | | | | | | | |
| **Availability of resources within the region** | | | | | | | |
| 31. Availability of required qualified labour within the region | | | | | | | |
| 32. Availability of the required materials within the region | | | | | | | |
| 33. Availability of the required plant within the region | | | | | | | |
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| **Competition (considering only the current project)** | | | | | | | |
| 34. Possible number of competitors passing the requirements | | | | | | | |
| 35. Desire of qualified contractors to tender and win the project | | | | | | | |

| **Foreseeable future market conditions & firm’s financial situation** | | | | | | | |
|---|---|---|---|---|---|---|---|
| 36. Market’s direction (whether it is declining, expanding, etc.) | | | | | | | |
| 37. Amount of possible upcoming profitable projects out for tender in near future | | | | | | | |
| 38. Existing financial conditions indicating a financial risk in near future | | | | | | | |
| 39. Ratio of your firm’s current market share to the expected or aimed share | | | | | | | |
| **Client (considering long-term gains/losses)** | | | | | | | |
| 40. Amount of work the client carries out regularly | | | | | | | |
| 41. Amount of repeat business level that the client been following | | | | | | | |
| **Project (considering long-term gains and losses)** | | | | | | | |
| 42. Possible contribution to increase the contractor firm’s classification | | | | | | | |
| 43. Possible contribution to increase the firm’s identity and brand strength | | | | | | | |
| 44. Possible contribution in increasing firm’s market share and dominance in market | | | | | | | |
| 45. Possible contribution in building long-term relationships with other key parties | | | | | | | |
| 46. Contribution in maintaining long-term relations with important influence markets | | | | | | | |
| 47. Possible contribution in improving your firm’s staff expertise | | | | | | | |
| 48. Possible contribution to break into a new market with productive future | | | | | | | |
| 49. Contribution to firm’s future due to value of the completed project to the public | | | | | | | |
| **Consultant firm (considering long-term gains and losses)** | | | | | | | |
| 50. Amount of construction work the consultant has been carrying out regularly | | | | | | | |

Are there any additional factors you think are important? If so, please give reasons.

| |
|---|
| |

For your top three most important factors, please explain why you think they are most important.

| |
|---|
| 1. |

| |
|---|
| 2. |
| 3. |

7. For your three least important factors, please explain why you think they are not important.

| |
|---|
| 1. |
| 2. |
| 3. |