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Validating a Hybrid Multi-Criteria Decision-Making Model for Private Partner Selection in PPP Using Monte Carlo Simulation

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Abstract

Effective private partner selection is fundamental to the success of Public-Private Partnership, particularly in environments characterised by uncertainty and complexity. This study develops and validates a Hybrid Multi-Criteria Decision-Making framework that integrates Fuzzy Analytical Hierarchy Process, Best-Worst Method, Analytic Network Process and the Technique for Order of Preference by Similarity to Ideal Solution. The integrated approach accommodates judgmental vagueness, ensures internal consistency of criteria weights, addresses interdependencies and facilitates comprehensive prioritisation of private partners. To test the reliability and sensitivity of the proposed model under variable conditions, Monte Carlo simulation was employed. This simulation introduced stochastic variation to the input parameters. Java was adopted to implement the simulation process due to its computational efficiency and object-oriented modularity. A total of 10,000 iterations were run, with each criterion weight treated as a normally distributed variable, assuming a standard deviation of 5% of its mean. The stability of rankings observed across all simulation iterations affirms the model's structural predictive consistency. By quantifying the impact of input uncertainty, the model offers decision-makers enhanced confidence in the selection process. The findings advocate for the adoption of the framework, validated through simulation, as a critical tool for advancing transparency, defensibility and resilience in PPP procurement.

Keywords: Public-Private Partnerships (PPP), private partner selection, multi-criteria decision-making (MCDM), Monte Carlo simulation, model validation, hybrid decision model, uncertainty analysis

Introduction

Monte Carlo simulation is a suitable choice for model validation because it allows for accessibility of how sensitive a model's outcomes are to changes in the input criteria weights (Seila, 1982). Monte Carlo simulation is a robust statistical method that utilizes repeated random sampling to simulate and analyze the impact of uncertainty in models and decision-making processes (Lo, Pan and Wu, 2021; Díaz et al., 2022). In the context of validating a model for the selection of private partners in Public-Private Partnerships, Monte Carlo simulation can be used to assess the stability and robustness of the model's outcomes under varying conditions (Sadati, Zaukeri Getabi, and Rabbani, 2024). By introducing uncertainty into the decision criteria weights and other parameters, this approach allows for the exploration of how these uncertainties affect the final rankings of private partners (Dahri and Abida, 2017). This technique can be adopted to ensure that the results are robust and not unduly influenced by small changes or uncertainties in the pairwise comparisons or weightings. Sensitivity analysis also reveals how different changes in the weights of selection criteria affect the final rankings of private partners (Sadati et. al., 2024). If the rankings are stable despite small changes in weights, the model is considered robust. Also, project needs in PPP can vary greatly depending on the sector, location and stakeholders involved (Wang et. al., 2010; Zakeri et. al., 2024). Therefore, sensitivity analysis can help demonstrate how the decision model performs across different scenarios.

Literature review

Monte carlo simulation in model validation

The primary objective of using the Monte Carlo simulation in this research is to evaluate the sensitivity and robustness of the hybrid model by simulating different possible scenarios resulting from changes in the input data, such as the criteria weights and the associated performance ratings for each private partner (Serrano-Gomez and Munoz-Hernandez, 2019; Cui et al., 2023). This process will help validate whether the model consistently produced reliable outcomes or if slight variations in the inputs lead to significant changes in the rankings, which could indicate model instability or potential bias.

Steps for montecarlo simulation in model validation

Step 1: Define the Model Inputs

Based on the results from the AHP pairwise comparison, the weights for each of the

selection criteria are established. In the Monte Carlo simulation, these weights will be treated as variables with a defined probability distribution (such as normal distribution or uniform distribution) to account for uncertainty and variability in the judgment of experts (Yoo and Rho, 2021). Furthermore, the performance ratings of each private partner across the selection criteria are also inputs to the model. These ratings can vary due to the uncertainty in how partners perform or how expert opinions are framed (Gentile and Yee, 2015). Hence, a probability distribution is assigned to each input parameter (weights and ratings). For example, the financial criteria weight might be assigned a normal distribution around its mean value with a specified standard deviation, representing the uncertainty about its exact importance in the decision-making process (Zhu et al., 2019; Cui et al., 2023).

Step 2: Random Sampling of Input Variables

For each simulation run, random samples are drawn from the probability distributions defined for the criteria weights and performance ratings. These random samples represent potential real-world variations in the model's inputs. The number of iterations (simulations) should be sufficiently large to capture a wide range of possible outcomes, typically in the order of thousands to ensure the results' statistical significance (Zhu, et al., 2019; Cui et al., 2023).

Step 3: Calculate the Weighted Scores

For each set of randomly selected input values (weights and ratings), the weighted scores for each private partner are calculated using the formula:

$$\text{Weighted Score}_{\ i} = \sum_{j=1}^{n} \text{Weight}_j \times \text{Rating}_{ij}$$

where:

- Weight j is the weight of criterion j,
- Rating ij is the performance rating of partner i on criterion j,
- n is the total number of criteria.

This calculation is repeated for each iteration of the Monte Carlo simulation.

Step 4: Analysis

Once the simulation runs are completed, the distribution of the weighted scores for each private partner is generated. This provides an empirical representation of how the partners' rankings fluctuate under different input scenarios. The results are then analyzed to determine the stability of the rankings across different simulations. For instance, it might be observed whether a particular partner consistently ranks highest, or if the rankings change significantly depending on the sampled weights and ratings (Baptistucci, et al., 2018).

Step 5: Sensitivity and Robustness Check

The results of the Monte Carlo simulation can be used to determine which criteria have the most significant impact on the rankings. This can be done by tracking how the rankings change with respect to changes in the weights of each criterion. The simulation can also help identify any thresholds at which the rankings of private partners change significantly. If, for example, small changes in the financial criteria lead to dramatic shifts in the ranking of a particular partner, this may suggest that the model is overly sensitive to that input (Baptistucci, et al., 2018).

Implications for the model

By performing a Monte Carlo simulation, a deeper understanding of the variability and certainty/uncertainty inherent in the model is revealed. This validation technique not only demonstrates the model's robustness but also provides a clear picture of how sensitive the decision-making process is to changes in the criteria weights and partner ratings (Yoo and Rho, 2021). The results will allow decision-makers to better assess the reliability of the model and make more informed decisions regarding private partner selection in PPP projects.

Methodology

The Analytical Hierarchy Process (AHP), introduced by Saaty (1980), was adopted in this study as a robust decision-support tool for structuring and prioritizing complex criteria in the selection of private partners in Public-Private Partnership (PPP) infrastructure projects. AHP enables a problem to be broken down into a hierarchy of interrelated decision elements, facilitating both qualitative and quantitative assessment. It is particularly suited to contexts involving multiple stakeholder interests and limited information, such as PPP project environments (Saaty & Vargas, 2012; Hodge and Greve, 2017).

Table 1 Example of AHP pairwise comparison

	Criteria Area	Pairwise Scale of Importance																				Criteria Area
Pair 1	Criteria A	9	8	7	6	5		4	3	2		1		2	3	4		5	6	7	8	9	Criteria B
Pair 2	Criteria B	9	8	7	6	5		4	3	2		1		2	3	4		5	6	7	8	9	Criteria C
Pair 3	Criteria C	9	8	7	6	5		4	3	2		1		2	3	4		5	6	7	8	9	Criteria D

Source: Researcher's construct

This study applied AHP to determine the weights of key selection criteria, using a structured hierarchy that included five main criteria and associated sub-criteria, identified through a thorough literature review and consultations with PPP practitioners in Nigeria.

A purposive sampling technique was employed to identify and recruit participants with deep expertise and operational knowledge in PPP implementation. These included professionals from public authorities (ministries, departments and agencies), concessionaires and financial institutions. A total of 65 responses were received, of which 63 met the criteria for inclusion in the final analysis. This sample size aligns with established AHP studies, which typically involve smaller expert samples to preserve depth of judgement (Sutadian et al., 2017; Li & Zou, 2011; Elwakil, 2017).

Participants completed a structured questionnaire featuring pairwise comparisons of selection criteria, rated on Saaty's 1–9 semantic scale. The resulting pairwise matrices were analyzed using the Eigenvalue Method (EVM) to derive priority weights, selected for its ability to assess the consistency of expert judgements via the Consistency Index (CI) and Consistency Ratio (CR). Respondents were provided guidance to enhance the clarity and consistency of their responses.

Result

Development of a Multi-Criteria Decision-Making (MCDM) Model

A Multi-Criteria Decision-Making (MCDM) approach utilizing the Analytic Hierarchy Process (AHP) is central to the study, as it allows the decomposition of the complex partner selection process into hierarchical levels. AHP enables the determination of criteria weights through pairwise comparisons, ensuring consistency in expert judgments, which was validated using Consistency Index (CI) and Consistency Ratio (CR) calculations. The study employs the Eigenvalue Method (EVM) to derive priority vectors, ensuring that the decision-making framework is mathematically robust. Thereafter, a hybrid MCDM model was proposed, integrating four complementary techniques. To validate the model, a Monte Carlo simulation was conducted, introducing stochastic variations to assess the sensitivity and stability of the ranking outcomes. This technique tested the resilience of the partner selection framework by analyzing how variations in criteria weights and expert judgments impact final rankings. Sensitivity analysis further examined the influence of each criterion, ensuring that no single variable disproportionately skewed the results. The methodology ensures that the PPP partner selection model is both data-driven and contextually nuanced, enhancing its practical applicability for decision-makers in PPP procurement. Through the integration of structured statistical analysis and expert judgment validation, the study provides a rigorous, replicable and adaptable framework for selecting private partners in PPP projects, addressing key drivers and barriers while ensuring methodological robustness.

No single MCDM model can guarantee the accuracy and robustness of evaluation processes in engineering-related applications. Thus, a HYBD MCDM model was developed leveraging on the use of four multi-criteria decision-making algorithms for the sake of prioritizing private partners in PPP infrastructure projects. This study employs a

hybrid multi-criteria decision-making (MCDM) model to evaluate and rank private partners in PPP projects. It begins with Fuzzy AHP to derive weights for evaluation criteria while handling expert judgment uncertainty. BWM is then used to validate and refine these weights with fewer comparisons and higher consistency. ANP follows to account for interdependencies among criteria, producing adjusted priorities. TOPSIS ranks the private partner alternatives based on proximity to ideal solutions.

Optimized Private Partner Selection Model (OPPSM)

$$C_i = \frac{\sqrt{\sum_{j=1}^{n}\left(w_j' \times r_{ij} - v_j^-\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j' \times r_{ij} - v_j^+\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j' \times r_{ij} - v_j^-\right)^2}}$$

where:

- w_j' = final adjusted weight from Fuzzy AHP + BWM + ANP
- r_{ij} = normalized score
- v_j^+, v_j^- = ideal/anti-ideal solution for each criterion
- C_i = final score for ranking alternative i

The developed Hybrid MCDM model was applied to evaluate six hypothetical private partner cases in order to demonstrate its effectiveness and practical utility in partner selection for PPP projects. In this section, the results of the evaluation are presented, including detailed analyses of both the weighted and unweighted performance scores for each private partner.

These weighted criteria scores were then normalized to ensure comparability across different scales. Subsequently, the normalized weights were applied to the performance scores assigned to each private partner across the evaluation criteria.

For each private partner, the average normalized weighted score was calculated by taking the mean of the weighted scores across all criteria. This provided a single aggregated performance score for each private partner, facilitating direct comparison and ranking.

The detailed findings from this process, including the comparative performance of each private partner, are presented in the following subsections, along with a critical discussion of the implications of the results for PPP project partner selection.

Monte Carlo Simulation

To validate the accessibility of how sensitive the model's outcomes are to changes in the input criteria weights, the Monte Carlo simulation was applied as described in Section 3.2. By introducing uncertainty into the decision criteria weights and other parameters, this approach allows for the exploration of how these uncertainties affect the final rankings of private partners (Jagtap and Mahajan, 2024). Firstly the total weights of all the private

partners were calculated using 6 hypothetical cases. The developed model was used to calculate the final scores of each private partner.

Table 2

Private Partner	Ci Score
A	0.6768
B	0.4369
C	0.4669
D	0.7202
E	0.3124
F	0.4110

Thereafter, java was used to generate simulations for the analysis. The Monte Carlo simulation technique relies on the generation and analysis of a large number of random samples to model uncertainty. Java presents a balanced combination of performance, object-oriented design and platform independence which makes it particularly well-suited for developing applications that involve uniform random number generation, sampling from statistical distributions and comprehensive output analysis.

One of the foremost advantages of using Java lies in its powerful built-in support for random number generation. Java's object-oriented programming model is another factor that supports its adoption for Monte Carlo simulations. The language enables modular and reusable code structures, allowing simulation components such as input configuration, random sampling, simulation logic and result analysis to be encapsulated in classes and reused across different simulation scenarios. This modularity not only improves code maintainability and readability but also enhances the scalability of the simulation framework for more complex systems.

Table 3

Private Partner	count	mean	std	min	5%	25%	50%	75%	95%	max
D	10000	61.510	3.047	48.468	56.527	59.443	61.508	63.588	66.513	74.953
A	10000	55.987	2.837	45.074	51.297	54.076	56.000	57.912	60.667	66.187
C	10000	58.930	2.938	47.835	54.155	56.951	58.915	60.882	63.735	70.236
B	10000	56.277	2.806	45.598	51.709	54.381	56.296	58.151	60.979	67.224
E	10000	59.445	2.979	48.299	54.537	57.433	59.431	61.477	64.300	71.176
F	10000	52.471	2.680	43.160	47.949	50.648	52.519	54.277	56.791	62.483

To assess the robustness of private partner selection scores under conditions of uncertainty, a Monte Carlo simulation was conducted using 10,000 iterations. The simulation modelled the potential variability in the original scores by treating each score as a stochastic variable following a normal distribution. The mean of each distribution was set to the original performance score of the partner, while the standard deviation was defined as 5% of that score, reflecting moderate variability in selection criteria judgments.

The results, summarized in Table 3, provide descriptive statistics for each of the six private partners, including the mean (expected performance), standard deviation (variability) and key percentiles (5th, 25th, 50th, 75th and 95th), which offer insights into the potential best-case and worst-case scenarios for each partner.

The analysis reveals that Partner D consistently outperforms others, with the highest mean simulated score of 61.47 and a 95th percentile value reaching 66.62, indicating strong performance even under optimistic conditions. However, Partner D also shows relatively high variability (standard deviation: 3.10), suggesting that its performance is more sensitive to changes in underlying criteria.

Partner E and Partner C follow closely, with mean scores of 59.38 and 58.88, respectively. Both exhibit lower variability than Partner A, with standard deviations of 3.00 and 2.94, indicating more stable performance across simulations. Their 5th percentile values (54.49 for E and 54.02 for C) demonstrate comparatively strong resilience under conservative scenarios.

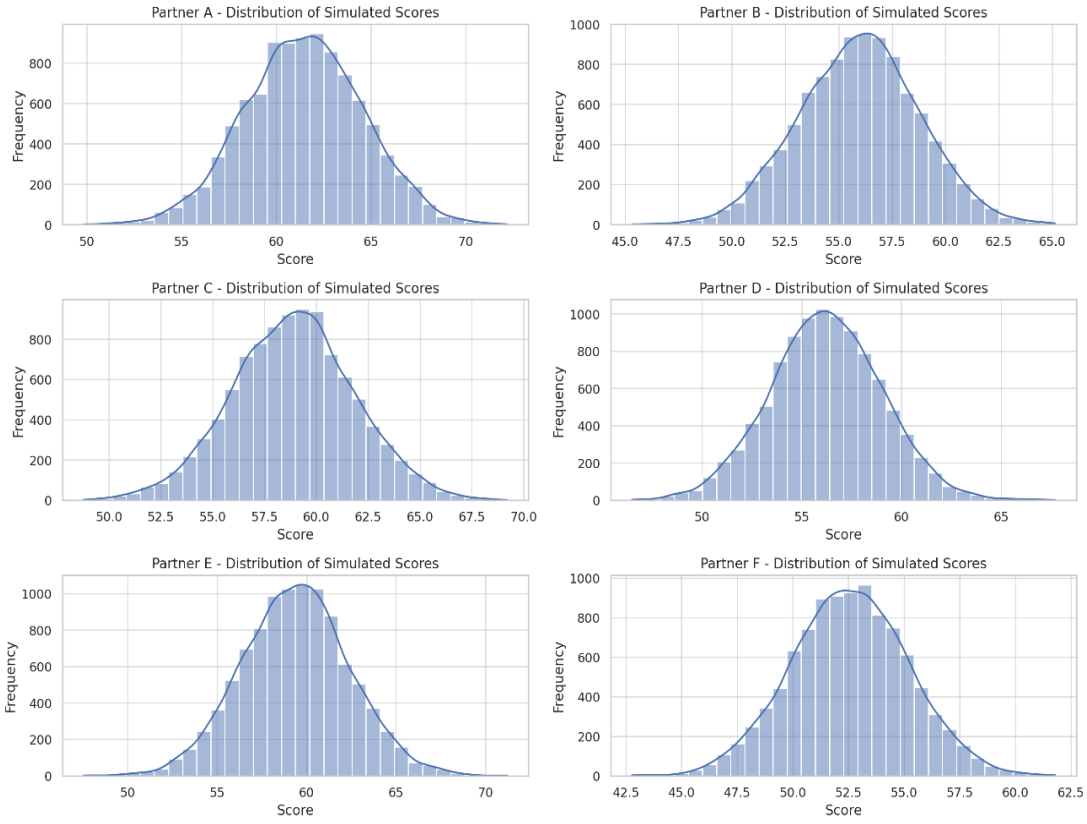


Figure 1: Distribution of simulated scores

The histogram analysis provides a visual representation of the risk and variability associated with each partner's selection. Notably, Partner D consistently ranks as the top performer with minimal deviation, making it a highly reliable candidate under uncertainty.

These insights offer valuable input for decision-makers, supplementing deterministic MCDM results with probabilistic evidence. The use of Monte Carlo simulation thus enhances confidence in the robustness of partner selection by quantifying the effects of potential input uncertainties. The histograms presented above depict the frequency distribution of simulated scores for each private partner. Partner A and D exhibit relatively narrow and high-peaked distributions, centered around their high mean scores of 0.6768 and 0.7202, respectively. This indicates that under uncertainty, their performance remains consistently strong, with limited variation. The clustering of scores around the upper bounds reflects a high level of robustness in their evaluations. Partner B and C show moderate distribution spread, with lower mean scores (0.4369 and 0.4669, respectively). While their histograms are more dispersed compared to A and D, the bulk of simulated values remains in a mid-performance range, indicating medium stability under changing input conditions. Partner E and F, having the lowest base scores (0.3124 and 0.4110), also demonstrate relatively dispersed distributions, but skewed towards the lower end. These distributions highlight their consistently poor performance even when uncertainties are introduced. Their wide spread suggests a higher sensitivity to input variability, reinforcing their unsuitability in scenarios requiring reliable performance.

The ranking of the partners remains consistent across these simulations, indicating that the model is reliable. The model appears effective in providing a clear, reliable ranking of private partners. The minimal changes in the rankings across scenarios suggest that the criteria weightings are fairly balanced and that no single factor is overly dominant in determining the outcomes. The fact that modest variations in the criteria weights do not cause drastic shifts in rankings means the model is robust and can adapt to different stakeholder preferences or policy priorities without fundamentally changing the outcomes. This is a critical aspect for decision-makers, as it suggests that the model can be used in real-world settings with a high degree of confidence. Furthermore, the consistency across all scenarios demonstrates that the model's outcomes are not overly dependent on any one parameter. This is ideal for practical application, as it indicates that the model can produce stable, reliable results even when minor adjustments are made.

Conclusion

This study validated the Hybrid Multi-Criteria Decision-Making (MCDM) model developed for the selection of private partners in PPP infrastructure projects. The model integrated Fuzzy AHP, Best-Worst Method (BWM), Analytic Network Process (ANP) and TOPSIS to comprehensively address the complexity and interdependence of evaluation criteria. To assess the model's stability and reliability, Monte Carlo simulations were conducted using Java, introducing stochastic variations in input data to replicate real-world uncertainties.

The findings revealed that Partner D consistently emerged as the most suitable private partner, exhibiting high mean performance scores and stable rankings across 10,000

simulation iterations. Other top-performing partners, such as A and C, also showed resilience under varied scenarios, affirming the reliability of the model. The histogram and density plots supported these findings, indicating concentrated score distributions for top-ranked partners and dispersed, lower-bound distributions for underperforming ones.

Overall, the hybrid MCDM model supplemented by Monte Carlo simulations proved to be an effective tool for decision-makers, offering a balance between deterministic judgment and probabilistic insight. Its capacity to handle uncertainty, maintain ranking consistency and highlight performance sensitivity makes it a valuable framework for transparent and data-driven PPP procurement.

Recommendations

Based on the study's findings, the following recommendations are made:

Public agencies should consider employing hybrid decision-making frameworks that integrate Fuzzy AHP, BWM, ANP and TOPSIS to ensure comprehensive and balanced partner evaluations.

Incorporating Monte Carlo simulation in the evaluation process enhances decision-making reliability by exposing models to realistic uncertainties and stress testing their robustness.

Government bodies and private entities should invest in the development of automated decision-support systems using high-level programming languages like Java to facilitate reproducible, scalable and user-friendly simulations.

Training and capacity-building programs should be initiated to improve stakeholders' understanding of advanced MCDM and simulation techniques for evidence-based decision-making in PPP projects.

There is a need for policy frameworks that encourage the formal integration of MCDM and simulation-based validations in PPP selection processes to improve transparency and stakeholder confidence.

Limitations of the Study

While the study presents a comprehensive framework, several limitations must be acknowledged:

Use of Hypothetical Data: The evaluation of private partners was based on hypothetical case scenarios. Although useful for methodological demonstration, real-world validation may yield more context-specific insights.

Sample Size and Geographic Scope: The AHP-based weights were derived from a sample of 63 experts primarily within the Nigerian PPP context. Broader geographic sampling could enhance the model's generalizability.

Assumption of Normal Distribution: The Monte Carlo simulation assumed that input variables followed a normal distribution with a 5% standard deviation, which may not fully capture the range of real-world variability.

Computational Constraints: Although Java proved efficient, the simulation could benefit from parallel processing or integration with advanced simulation platforms for large-scale data analysis.

Suggestions for Future Research

To further strengthen and expand upon the contributions of this study, future research may consider the following directions:

Empirical Validation with Real Project Data: Future studies should apply the model to actual PPP projects across different sectors to validate its practical applicability and effectiveness.

Cross-Country Comparative Studies: Comparative research involving multiple countries could help explore how local institutional, economic and policy contexts influence the robustness of partner selection models.

Exploration of Alternative Probability Distributions: Researchers could investigate the effects of using other distributions in Monte Carlo simulations to better reflect the uncertainty characteristics of PPP environments.

Integration with Artificial Intelligence (AI): Future models could be enhanced by integrating AI and machine learning techniques to predict private partner performance and adaptively refine evaluation criteria.

Stakeholder Behaviour Modelling: Consider incorporating behavioural decision-making models to reflect how risk perception, negotiation dynamics and political considerations influence PPP partner selection.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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