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SELECTION OF OPTIMAL CONSTRUCTION SERVICE PROVIDER: A COMBINED DECISION FRAMEWORK WITH HYPERBOLIC FUZZY DATA

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Abstract. This study introduces an integrated decision-making framework for Construction Service Provider (CSP) selection, addressing limitations in traditional methods that prioritize cost over quality and holistic evaluation. The framework integrates "Hyperbolic Fuzzy Sets (HYFS)" to capture uncertainties in expert opinions, a variance method to weigh expert reliability, the "Logarithmic Percentage Change-driven Objective Weighting (LOPCOW)" method to determine criterion weights, and the "Weighted Aggregated Sum Product Assessment (WASPAS)" algorithm to rank CSPs. A case study involving five construction companies and fifteen criteria was conducted to validate the proposed framework. The framework proposed in the study is able to effectively rank the CSPs, demonstrating practical utility in selecting an optimal CSP considering both qualitative and quantitative factors. Sensitivity analysis showed the framework is robust to changes in criterion weights. It is to be noted that, "Experience", "Quality of work", and "Technology and Innovation" emerged as the top three categories of criterions influencing the selection process. The study contributes to the literature by introducing usage of HYFS to CSP selection problem, explicit computation of expert weights based on variance, LOPCOW for criterion weights, and an integrated HYFS-Variance-LOPCOW-WASPAS framework. The study offers a practical tool for stakeholders to move beyond cost-centric bidding, promoting fairness, efficiency, and accountability in project selection and various other decision-making contexts.

Keywords: construction service provider, hyperbolic fuzzy sets, LOPCOW, WASPAS, sustainability.

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1. Introduction

The construction industry has been a cornerstone of economic development for a long time, with large-scale infrastructure projects playing a very important role in shaping a nation's growth trajectory. In process, the Construction Service Provider (CSP) quoting the lowest bid is made the base for analysis and the lowest bidder tends to win the contract (Alkhateeb et al., 2021). This method, known as open tendering, has been the primary procurement method for both public and private sectors (Hanák et al., 2021). However, bidding strategies that overly prioritize cost-efficiency while overlooking qualitative factors, can lead to various challenges such as compromised project quality, delays, or even failures.

In recent years, this trend of considering only cost-efficiency has undergone a significant transformation. The procurement process for many infrastructure projects has shifted from purely cost-driven open tenders to negotiated tenders (Ellis et al., 2021). This shift promotes a more balanced approach, where projects are not solely granted to the lowest bidder but are instead awarded based on a Quality and Cost-Based Selection (QCBS) process. QCBS ensures that both the cost and qualitative aspects of a bid are meticulously evaluated, enabling the selection of CSPs who can deliver optimal outcomes. While QCBS enables optimal selection of CSPs, manually implementing it can be a cumbersome process that is subjective and prone to biases. As a result, integrating automated and systematic decision-support tools into this process is critical for achieving consistent and reliable outcomes.

To develop such systematic decision-making frameworks, advanced methodologies are used to objectively evaluate CSPs while handling uncertainty and ambiguity inherent in human judgments. Multi-Criteria Decision-Making (MCDM) systems provide a robust foundation for achieving these goals. By integrating mathematical models and expert inputs, MCDM systems enable the comprehensive assessment of CSPs, considering multiple criteria simultaneously.

The MCDM systems to be used in evaluating CSPs must exhibit the following characteristics:

1. A decision framework's aim should be to reduce the uncertainty present in the experts' views. For this the data obtained from the experts could be interpreted using fuzzy sets which are proven to be of help in handling uncertainty.
2. The relative importance of the experts must be captured in order to handle inconsistencies in expert given values. As in the decision-making scenarios, especially those involving multiple criteria, impact from cognitive fatigue or response bias can disproportionately influence the final outcome if not appropriately accounted for.
3. The importance of each criterion must also be effectively captured using a model that considers the relative importance of an expert. The computation methodology of criterion weights should also consider extremities that could be in the data.

The MCDM methodologies that have been developed and used for various service provider selection problems will be further examined in the literature review. Motivated by the forementioned characteristics that an effective decision framework for CSP selection must exhibit challenges identified through literature review for MCDM methodologies for service provider selection problems, this study implements the following:

1. The uncertainty is handled by adopting Hyperbolic Fuzzy Set (HYFS). HYFS is considered instead of earlier ortho-pair variants of fuzzy set, as HYFS provided extreme flexibility while overcoming limitations posed by earlier ortho-pair variants of fuzzy set under specific conditions (Dutta & Borah, 2023).
2. The relative importance of experts is captured using the variance method that effectively captures the hesitation and uncertainty present in the expert given criteria.
3. The importance of the criteria is computed using the LOgarithmic Percentage Change-driven Objective Weighting (LOPCOW) which captures the extreme values effectively using a logarithmic operator (Ecer & Pamucar, 2022).
4. The rankings of CSPs are obtained using the Weighted Aggregated Sum Product Assessment (WASPAS) method which provides a rank index using two models: weighted sum and product (Zavadskas et al., 2012).

The aim of this study is to propose a combined decision framework that interprets expert opinion data using HYFS, determines the weights of experts using variance method, and weights of criteria using LOPCOW, and finally ranks CSPs using WASPAS. Through the proposed framework, the challenges identified in the literature review are tackled effectively, thus contributing to the literature.

2. Literature review

In this section, the literature regarding MCDM methods for service provider selection, evaluation criteria for service provider selection, HYFS, variance method, LOPCOW, and WASPAS are reviewed.

2.1. MCDM methods for construction industry service provider selection

Multi-Criteria Decision-Making (MCDM) is a structured process that enables decision-makers to evaluate and prioritize competing criteria, aiding optimal decision-making across fields like operations research, management science, and engineering (López et al., 2023). The origin of MCDM can be traced back to early works of Von Neumann and Morgenstern (2007), game theory and decision theory. Over the years the MCDM methods evolved with various new methods being introduced, with these methods being adapted to various construction industry service provider/contractor selection and ranking problems.

Long (2025) proposed a MCDM framework for heritage building restoration, integrating the fuzzy Best-Worst Method (BWM) and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank contractors based on 12 criteria identified through a survey. The decision framework was applied to a case example in Vietnam, with the model utilizing Triangular Fuzzy Numbers (TFNs). Hallak (2024) developed a hybrid MCDM framework for evaluating construction suppliers in conflict-affected regions, integrating fuzzy goal programming, geographical information systems-based risk assessment, and fuzzy Analytic Hierarchy Process (AHP). The model applied to a real-world supplier selection case example with 15 selection criteria addressing economic, technical, and humanitarian factors, and thus demonstrating its usage in both conflict and stable settings. Nithya et al. (2024) proposed the Digital Weighted Multi-Criteria Decision-Making (DWMCDM) method, using interval-valued fuzzy sets (IVFS) to select contractors by evaluating prequalification and bid phases. The method proposed calculated the digital weighted distances to assess criteria alignment in the first phase and ranks contractors in the second phase based on bid price and weighted distances. Hakimi et al. (2024) introduced a fuzzy Utilities-Additives STAR (UTASTAR) method to address the complexity of sustainable supplier selection in the construction industry, emphasizing environmental, financial, and social responsibilities. By evaluating utility functions and comparing results with other MCDM models, the study demonstrated that the fuzzy UTASTAR is capable for producing reliable rankings. Fawzy et al. (2024) proposed a MCDM strategy for contractor selection in real-world case example of Egypt's large-scale construction projects, moving beyond the "lowest-price-wins" approach. The study used AHP to calculate prequalification criteria weights and applying TOPSIS and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) to rank contractors and also demonstrated that expertise and safety standards are the highly preferred factors in selecting contractors by decision-makers, thus they significantly influence rankings. Santos et al. (2025) developed a framework that integrated Geographic Information Systems (GIS), Building Information Modeling (BIM), and Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) to support infrastructure investment planning through comprehensive evaluations of various criterions. Shume and Mitikie (2024) developed an alternative contractor selection model for public building projects in Ethiopia by integrating the Delphi and fuzzy AHP methods. In the study 30 sub-criteria were selected using literature review and were then further categorized into six main categories using Delphi method. The fuzzy AHP method assigned weights to the criteria revealed that Bid Price, timely project completion, experience with similar projects, and staff qualifications are the most important factors. Ghafoori and Abdallah (2024) developed a material and supplier selection model that integrated TOPSIS with updatable databases of materials and suppliers. The factors used by the study to rank the suppliers were project characteristics, supplier attributes, and material performance. Deepika et al. (2023) developed a comprehensive supplier selection model for the construction industry, addressing limitations of traditional methods by incorporating fuzzy Delphi, fuzzy AHP, and fuzzy TOPSIS. The study focused on selecting the best M-Sand suppliers, using fuzzy Delphi to identify key criteria, fuzzy AHP to assign weights, and fuzzy TOPSIS to rank suppliers. The model also used Data Envelopment Analysis (DEA) to further enhance the evaluation by considering both the qualitative and quantitative criterions. Kiani Mavi et al. (2025) identified 19 critical success factors of construction projects in New Zealand, and used fuzzy "decision-making trial and evaluation laboratory (DEMATEL)" approach to find interrelationships between these factors.

The characteristics of the methodologies used in the above-mentioned studies have been summarized in Table 1.

The studies reviewed above, revealed that various MCDM frameworks have been developed and used to model problems in the context of construction service provider selection. While these studies provide valuable insights in modelling problem of similar nature, several limitations and research gaps become apparent. The most notable research gap being lack of consideration towards the relative importance of experts. In decision-making processes that rely on multiple criteria, the expertise and credibility of those providing evaluations are as important as the criterions themselves. The knowledge, experience, and familiarity with the problem domain, directly influences the reliability of expert assessments. A limitation that can be noted in the literature is use of TFNs. While TFNs are valued for their simplicity and computational efficiency, they may not always be suitable for modelling nonlinear fuzzy problems that are often encountered in real-life scenarios (Jagadeeswari & GomathiNayagam, 2017). Furthermore, existing studies do not provide personalized ranking, where rankings are determined individually for each expert, providing a clear understanding of each expert's unique perspective. This limits the granularity of the analysis, as it only considers the collective evaluation of the experts without acknowledging variations in expert preferences and judgments. Additionally, extremities and inconsistencies in expert opinions, where some experts

Table 1. Comparison of decision frameworks in existing literature in the context of construction service provider selection

Literature	Uncertainty modelled using fuzzy	MCDM framework used	Criteria weights	Expert weights	Consideration of extreme attitudes for criteria weights computation	Personalized rankings
Long (2025)	Modelled using TFNs	BWM-TOPSIS	✓	✗	✗	✗
Hallak (2024)	Modelled using fuzzy	Goal programming-AHP	✓	✗	✗	✗
Nithya et al. (2024)	Modelled using IVFS	DWMCDM	✓	✗	✗	✗
Hakimi et al. (2024)	Modelled using TFNs	UTASTAR-VIKOR	✓	✗	✗	✗
Fawzy et al. (2024)	Not modelled	AHP-TOPSIS-VIKOR	✓	✗	✗	✗
Shume and Mitikie (2024)	Modelled using TFNs	Delphi-AHP	✓	✗	✗	✗
Deepika et al. (2023)	Modelled using TFNs	Delphi-AHP-TOPSIS-DEA	✓	✗	✗	✗

may be overly optimistic or pessimistic, have not been adequately addressed in existing literature.

The selection criteria considered in this study for CSP prioritization are broadly classified into experience, cost/budget, quality of work, safety measure, environmental impact, and technology innovation. Within these categories, we have 15 sub-criteria that facilitate CSP prioritization. Details on these selection criteria are presented in further section for clarity to readers. Notably, the criteria consider sustainability aspects during assessment as the CSP selection is driven by green practices and several sub-criteria within the main category specifically focus on such green practices owing to emphasis from global leaders to mitigate carbon footprint from construction sector significantly.

2.2. Hyperbolic fuzzy set, LOPCOW, and WASPAS

HYFS was introduced by Dutta and Borah (2023) to extend traditional fuzzy set variants such as q-rung orthopair fuzzy sets by constraining the product of membership and non-membership degrees to be less than or equal to one. This product-based constraint offers a greater flexibility in representing uncertainty compared to the traditional sum-based constraints. Dutta and Borah (2023) also demonstrate the use of HYFS in a COVID-19 associated decision-making problem. Alamoodi et al. (2024) explored the integration of HYFS in MCDM for Agriculture 4.0 Decision Support Systems (ADSS) selection, highlighting its robustness in managing imprecise information.

The LOPCOW introduced by Ecer and Pamucar (2022) is a method for assigning weights to criteria. LOPCOW provides a relatively balanced weight allocation to the criteria since it has a smaller ratio difference between the most and least important criteria. The LOPCOW method has been widely adopted by the MCDM community for modelling criterion weights in various decision problems. For instance, Ecer et al. (2023) has used LOPCOW to assign criteria weights for the problem of selecting the optimal micro-mobility solutions to be integrated into urban transportation systems. Nila and Roy (2023) developed a MCDM framework that used fuzzy LOPCOW for obtaining criteria weights in a case involving optimal third-party logistics (3PL) provider selection problem for a food manufacturing company in India. Simic et al. (2023) had used LOPCOW for determining objective importance of criterions in a decision-making tool that supports decisions related to warehouse management system (WMS) and Industry 4.0-based solutions for a company from the Serbian grocery retail sector. Ulutaş et al. (2023) developed a decision-making framework for prioritization of insulation materials that improve a building's thermal performance. The decision-making framework developed integrated LOPCOW for computation of criteria weights. Ulutaş et al. (2024) had integrated LOPCOW in a grey MCDM framework for assigning attribute weights in a multidimensional 3PL selection decision problem. Guo et al. (2024) introduced a novel machine learning based MCDM that used LOPCOW for objective weight computation for criteria, in a case study that involves policy recommendations for the European Union. Rong et al. (2024) developed a Failure mode and effect analysis (FMEA) model for risk prioritization using LOPCOW for estimating importance of risk factors and the Additive Ratio Assessment (ARAS) method. Korucuk et al. (2024) had proposed a framework that used Interval-valued Fermatean Fuzzy (IVFF) LOPCOW to obtain criteria weights in a real case study of decision problem involving humanitarian warehouse site selection.

The WASPAS algorithm introduced by Zavadskas et al. (2012) is a ranking method that improves upon traditional methods by combining two simpler models: Simple Additive Weighting and Weighted Product Method to rank the alternatives. The WASPAS method has been used by the MCDM community extensively for the purpose of ranking alternatives in various decision problems. For example, Aydin et al. (2022) adapted WASPAS and applied to the decision problem of selection of optimal location for a new mobility hub location in Istanbul. Masoomi et al. (2022) had developed an integrated framework that used BWM and WASPAS for evaluating and selecting renewable energy supply chain supplier strategically. Görçün et al. (2024) developed a novel decision framework for tramcar selection problem in the urban transport. The decision framework developed used Power-Heronian based WASPAS for ranking the alternatives. Dhumras and Bajaj (2024) used a q-rung picture fuzzy sets based AHP-WASPAS decision framework to model the prioritization decision problem for potential strategic plans in green supply chain management system. Naz et al. (2025) developed a natural language processing-based decision framework that utilized WASPAS for product selection problem using on online product reviews. Ghorbani et al. (2025) has developed a decision framework that integrates WASPAS to evaluate and find the most dangerous section of the Kerman water conveyance tunnel and showed that the framework is capable of evaluating hazards in a tunnelling project from geotechnical aspects. Zavadskas et al. (2025) presented hyperbolic fuzzy WASPAS for construction contract dispute mitigation. Ji et al. (2025) introduced four novel operators and integrated LOPCOW and WASPAS to develop decision framework for selection problems. The decision framework was applied to a mid-sized manufacturing company to evaluate smart technologies to be implemented in the company.

The review of existing literature highlights the significance of HYFS, the LOPCOW method, and the WASPAS approach in MCDM research. HYFS has demonstrated superior flexibility in handling uncertainty and has been successfully applied to complex decision problems, including COVID-19 response strategies and Agriculture 4.0 Decision Support Systems. The LOPCOW method has proven to be an effective criterion weighting method and is being widely adopted in decision making frameworks for various decision problems, including the decision problems involving transportation, logistics, warehouse management, and policy evaluation. Its ability to balance weight distributions while accounting for any extremities in expert data makes it a preferred choice for objective weight computation in diverse MCDM frameworks. Similarly, WASPAS has established itself as a robust ranking method, leveraging the strengths of both additive and multiplicative models. Its applications range from infrastructure planning and energy sector decision-making to sustainable supply chain management and technology selection. The widespread integration of these methods into real-world decision scenarios is the proof of their adaptability and effectiveness in managing complex, uncertain, and multidimensional problems.

3. Methodology

In this section, the research methodologies and the decision-making frameworks used to evaluate CSPs while considering multiple criteria simultaneously have been described.

3.1. Preliminaries

Some basic concepts about HYFS are discussed below.

Definition 1 (Dutta & Borah, 2023): For a reference set R, a HYFS H_R is given by

$$H_R = \{r, \mu_h(r), v_h(r) \mid \forall r \in R\}; \tag{1}$$

$$\mu_h(r), v_h(r) \in [0,1]; \tag{2}$$

$$0 \le \mu_h(r) \cdot v_h(r) \le 1, \tag{3}$$

where $\mu_h(r)$ represents the degree of optimism/membership, and $v_h(r)$ represents the degree of pessimism/non-membership for a given element $r \in R$.

Definition 2 (Dutta & Borah, 2023): The degree of indeterminateness $\aleph(H)$ of a HYFS H_R is given by

$$\aleph(H_R) = 1 - \mu_h(r) \cdot v_h(r), \ \forall r \in R. \tag{4}$$

Definition 3 (Dutta & Borah, 2023): The score function and accuracy function of a HYFS H_R is given by

$$S(H_R) = 2\mu_h(r) - \mu_h(r) \cdot v_h(r), \ \forall r \in R; \tag{5}$$

$$A(H_R) = 2v_h(r) - \mu_h(r) \cdot v_h(r), \ \forall r \in R, \tag{6}$$

where $S(H_R)$ represents the score function, and $A(H_R)$ represents the accuracy function of the HYFS H_R respectively.

3.2. Expert weight estimation using variance

The expert weights are estimated using the variance present in data given by the experts. The assumption used in this method is that an expert's reliability is directly proportional to the variability in their assessments. Higher variance in expert given data reflects a broader range of evaluations, suggesting the expert has considered a more diverse set of perspectives in their judgment. Thus, experts with greater variability in their data are assigned higher weights. Whereas, lower variance in expert given data might indicate cognitive fatigue and response bias. The steps for computing expert weights using variance are as follows.

Step 1: A decision matrix $A^{(e)} = \left[a_{ij}^{(e)}\right]_{m \times n}$ is to be constructed for each expert e, where $a_{ij}^{(e)}$ is the value given by the expert for the i^{th} alternative on the j^{th} criterion. Here $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$.

Step 2: For each row i in $A^{(e)}$, the variance of the values should be calculated using Eqn (7):

$$Var_i^{(e)} = \frac{1}{n}\sum_{j=1}^{n}\left(a_{ij}^{(e)} - \bar{a}_i^{(e)}\right)^2, \tag{7}$$

where $Var_i^{(e)}$ is the variance, and $\bar{a}_i^{(e)} = \frac{1}{n}\sum_{j=1}^{n} a_{ij}^{(e)}$ is the mean of i^{th} row of the matrix $A^{(e)}$.

Step 3: Sum the variances of all rows to find the total variance of an expert:

$$S^{(e)} = \sum_{i=1}^{m} Var_i^{(e)}, \tag{8}$$

where $S^{(e)}$ is the total variance of expert e.

Step 4: Repeat step 1–3 are to be repeated for all experts $e = 1, 2, 3, \ldots, k$.

Step 5: Normalize the total variances to obtain the expert weights:

$$WK^{(e)} = \frac{S^{(e)}}{\sum_{e=1}^{k} S^{(e)}}, \tag{9}$$

where $WK^{(e)}$ is the weight to be assigned to the expert e, $0 \le WK^{(e)} \le 1, \forall e$, and $\sum WK^{(e)} = 1$.

3.3. Estimation of criteria weight using LOPCOW

In this section the steps for estimating the weights of criterions are presented. The LOPCOW method proposed by Ecer and Pamucar (2022) is adapted for estimating the criterion weights. The steps adapted from the method in this study are as follows:

Step 1: A decision matrix $L = \left[l_j^{(e)}\right]_{k \times n}$ is to be constructed, where $l_j^{(e)}$ is the rating given by the expert e for the j^{th} criterion. Here $j = 1, 2, 3, \ldots, n$ and j can either be a cost criterion or benefit criterion.

Step 2: Normalize the L matrix. The linear max-min normalization technique proposed by Ecer and Pamucar (2022) is to be used to obtain the normalized matrix $N = \left[g_j^{(e)}\right]_{k \times n}$.

$$g_j^{(e)} = \begin{cases} \dfrac{\left(l_j^{(e)} - \min\left(l_j\right)\right)}{\left(\max\left(l_j\right) - \min\left(l_j\right)\right)}, & \text{if } j \text{ is benifit criterion} \\[2ex] \dfrac{\left(\max\left(l_j\right) - l_j^{(e)}\right)}{\left(\max\left(l_j\right) - \min\left(l_j\right)\right)}, & \text{if } j \text{ is cost criterion} \end{cases}, \tag{10}$$

where l_j corresponds to the column of criterion j.

Step 3: The percentage value for each criterion based on their normalized evaluations of all experts is to be computed.

$$P_j = \ln\left(\frac{\sqrt{\frac{\sum_{e=1}^{k}\left(g_j^{(e)}\right)^2}{k}}}{\sigma_j}\right)\times 100, \quad (11)$$

where P_j represents the percentage value for the criterion j, and σ_j represents the standard deviation of g_j for the j^{th} criterion. The formula captures the overall magnitude of evaluations of a criterion. The natural logarithm is used to smoothen the extreme evaluations and ensuring balanced weights. The multiplication by 100 in the formula is done to enhance interpretability and comparability of the percentage values.

Step 4: Compute the weights for each criterion based on their percentage values to ensure that the contributions of all criterions are proportionate and sum up to 1. The formula is:

$$WC_j = \frac{P_j}{\sum_{j=1}^{n} P_j}, \quad (12)$$

where WC_j is the criterion weight corresponding to the j^{th} criterion. The Eqn (12) yields a vector of dimension $1\times n$.

3.4. Rank estimation using WASPAS

In this section the steps for estimating the ranks of a given set of alternatives and decision matrix are presented. The study adapts the WASPAS method proposed by Zavadskas et al. (2012). The steps adapted from the method in this study are as follows.

Step 1: A decision matrix $A^{(e)} = \left[a_{ij}^{(e)}\right]_{m\times n}$ is to be constructed for each expert e, where $a_{ij}^{(e)}$ is the value given by the expert for the i^{th} alternative on the j^{th} criterion. Here $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$. The j^{th} criterion could either be of the cost category or benefit category.

Step 2: Normalize the columns corresponding to the j^{th} criterion using Eqn (13), if the criterion is of benefit category, if it belongs to the cost category normalize it using Eqn (14):

$$\hat{a}_{ij}^{(e)} = \frac{a_{ij}^{(e)}}{\max\left(a_j^{(e)}\right)}; \quad (13)$$

$$\hat{a}_{ij}^{(e)} = \frac{\min\left(a_j^{(e)}\right)}{a_{ij}^{(e)}}, \quad (14)$$

where $\hat{a}_{ij}^{(e)}$ is the normalized value of $a_{ij}^{(e)}$ for alternative i on criterion j, given by expert e.

Step 3: Find the weighted sum model using Eqn (15):

$$WSM_i^{(e)} = \sum_{j=1}^{n} \hat{a}_{ij}^{(e)} \cdot WC_j, \quad (15)$$

where $WSM_i^{(e)}$ is the weighted sum for alternative i, using decision matrix of expert e.

Step 4: Find the weighted product model using Eqn (16):

$$WPM_i^{(e)} = \prod_{j=1}^{n}\left(\hat{a}_{ij}^{(e)}\right)^{WC_j}, \quad (16)$$

where $WPM_i^{(e)}$ is the weighted product for alternative i, using decision matrix of expert e.

Step 5: Compute the ranking value using Eqn (17):

$$RV_i^{(e)} = \alpha WSM_i^{(e)} + (1-\alpha) WPM_i^{(e)}, \quad (17)$$

where $RV_i^{(e)}$ is the ranking value for alternative i, using decision matrix of expert e, and α is a parameter such that $\alpha \in [0,1]$. The ranks with respect to expert e are then computed by assigning 1 to the highest $RV_i^{(e)}$, and m to the lowest $RV_i^{(e)}$.

Step 6.1: Applying steps 1–5 for decision matrix of each expert, k vectors of dimensions $1\times m$ are obtained. To obtain the final ranking a rank fusion procedure that considers the expert weights is used.

Step 6.2: Let the outputs of applying steps 1–5 for each expert e be aggregated into a single matrix $RS = \left[rs_i^{(e)}\right]_{k\times m}$, where the $rs_i^{(e)}$ represents the rank assigned to alternative i using the decision matrix of expert e.

Step 6.3: Aggregated rank values for each alternative i is obtained using Eqn (18):

$$ars_i = \sum_{e=1}^{k} rs_i^{(e)} \cdot WK^{(e)}, \quad (18)$$

where ars_i is the aggregated rank values for each alternative i, and $WK^{(e)}$ is the expert weight of the expert e.

Step 6.4: Let $ARS = \left[ars_i\right]_{i\times 1}$. The inverse of aggregated rank values is to be found using Eqn (19), so that highest value gets assigned rank one, and the lowest value gets assigned rank m:

$$iars_i = \max(ARS) - ars_i, \quad (19)$$

where $iars_i$ is the inverse aggregated rank values for each alternative i. By performing the Eqn (19), the value of $iars_i$ whose ars_i is the max ARS, becomes zero. The $iars_i$ of the alternatives are used compute the final ranking of the alternatives, such that the alternative with highest $iars_i$ gets assigned rank one.

3.5. Complete workflow of the framework

The decision framework proposed and used in the study has been briefed in form of a workflow in the Figure 1, to help better understand the framework. The panel of k experts are stakeholders who are familiar with the nuances of the decision problem concerned. These k experts give their ratings on relevance of n criterions. Then these k experts give their rate of m alternatives over the n criterions. The weights of experts form a vector of dimension $1\times k$, and is estimated using the steps mentioned in Section 3.2.

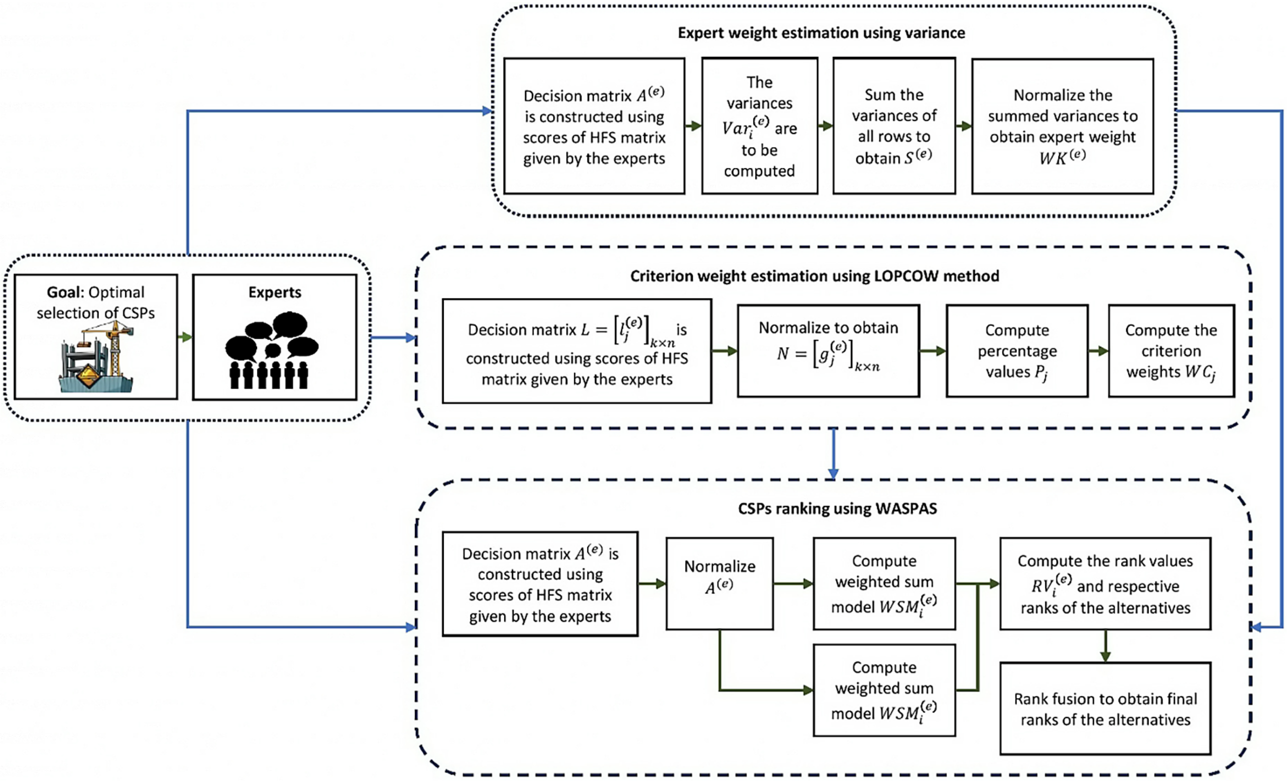

Figure 1. Workflow diagram of the proposed framework

The weights of the criterions form a vector of dimension $1\times n$, and is estimated using the steps mentioned in Section 3.3. The criterion weights are then used to determine rankings of each alternative as given by an individual expert, thus together forming a matrix of dimension $k\times m$. The rankings given by the individual experts and then fused using expert weights thus obtaining the final rankings of the alternatives. The procedure for rank estimation and fusion is given in Section 3.4. The application of the decision framework is tackled in the next section in form of a case study.

4. Case example

In this study a case example is presented, which focuses on the CSP selection problem for a new infrastructure development project among five alternative construction companies based in India. The study aims to assist the government and stakeholders in selecting the optimal CSP for their project based on a quality-cum-cost scenario. For brevity the five alternatives are hereon referred to as A1, A2, A3, A4 and A5. The CSPs A1, ..., A5 are to be evaluated based on six main criteria which are further divided into 15 sub criterions C1, C2, ..., C15. These criteria have been summarized in Table 2.

4.1. Data

A panel of stakeholders in the construction industry with substantial work was formed through convenience sampling. A questionnaire to collect their rating on the criterions and the alternatives was designed using a custom 7-element scale while taking into consideration the suggestions of the panel members. The linguistic terms used in the scale for collecting rating on alternatives were: Strongly Disagree (SD), Disagree (D), Slightly Disagree (SLD), Neutral (N), Slightly Agree (SLA), Agree (A), and Strongly Agree (SA). The linguistic terms used in the scale for collecting rating on the criterions were Not Relevant (NR), Slightly Relevant (SLR), Somewhat Relevant (SR), Neutral (N), Moderately Relevant (MR), Very Relevant (VR), and Extremely Relevant (ER). Table 3 provides ratings on the CSPs A1, ..., A5 and Table 4 provides ratings on the criterions C1, ..., C15 given by the four experts that constitute the panel.

4.2. Application of the proposed framework on the case

The proposed framework involves assessing the CPSs using criterions, in order to select an optimal CSP for a given construction project. Steps that were used to apply the proposed decision framework on the case example are as follows.

Step a: Four decision matrices of dimension 1×15, each corresponding to an expert is to be formed for assessing the alternatives, and a decision matrix of dimension 4×15 is to be formed for assessing the criterions. The decision matrices are to be interpreted through HYFS, and the values are to be then converted to scores using Eqn (5). Table 5 and Table 6 present the HYFS values that are used in the study and the corresponding HYFS scores computed for ratings on alternatives and ratings on criteria respectively.

Table 2. Criteria and sub-criteria considered for ranking the alternatives

Source	Criterion	Sub-criterion	Symbol	Type
Chen et al. (2021)	Experience	Project portfolio	C1	Benefit
		Years of experience	C2	Benefit
		Reputation	C3	Benefit
Kishore et al. (2020)	Quality of work	Project success rate	C4	Benefit
		Compliance with standards	C5	Benefit
		Material quality	C6	Benefit
Anysz et al. (2021)	Cost and budget	Transparency in pricing	C7	Benefit
		Ability to stick to budget	C8	Benefit
Mohandes et al. (2020)	Safety measures	Compliance with safety regulations	C9	Benefit
		Accidents	C10	Cost
Ferrans et al. (2022)	Environmental impact	Sustainability	C11	Benefit
		Good impacts	C12	Benefit
		Bad impacts	C13	Cost
Wang et al. (2023)	Technology and innovation	Specialized project handling capability	C14	Benefit
		Innovation	C15	Benefit

Table 3. Alternative versus criterion data given by the decision panel

CSPs	Experts	Criterions														
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
A1	E1	N	SLA	SLA	N	A	A	A	A	A	SLD	A	SLA	A	N	A
	E2	SLA	SLA	SLA	N	N	N	N	N	N	N	N	N	N	N	N
	E3	SA	SA	SA	SA	SA	SA	SLD	A	SA	A	N	SA	SD	SA	SA
	E4	A	A	SA	SA	SA	SA	SA	SA	SA	N	A	A	SLA	SA	A
A2	E1	N	N	SLA	N	A	A	SLA	A	A	SLD	A	SLA	A	N	A
	E2	A	A	A	SA	SA	SA	A	A	SA	SLA	A	A	D	A	SA
	E3	SA	SA	SA	SA	A	SA	SLD	A	A	A	N	SA	SD	A	SA
	E4	A	SLA	SA	SA	SA	SA	SA	SA	SA	N	A	SLA	A	SA	SA
A3	E1	N	N	SLA	N	SLA	A	SLA	A	A	SLD	A	SLA	A	N	SLA
	E2	N	N	N	N	N	N	SLA	N	SLA	N	N	SLA	N	N	N
	E3	SA	SA	SA	A	A	SA	SLD	A	A	A	N	SA	SD	A	SA
	E4	SLA	SLA	SA	N	A	SA	A	SLA	SA	N	SLA	A	SA	A	SA
A4	E1	N	N	SLA	N	SLA	A	A	A	A	SLD	A	SLA	A	N	SLA
	E2	N	N	N	N	N	N	SLA	SLA	SLA	N	SLA	SLA	N	N	N
	E3	SA	SA	A	SA	A	SA	SLD	A	A	A	N	SA	SD	A	SA
	E4	SLA	SLA	SA	N	SA	SA	A	SLA	SA	N	SLA	A	A	SA	SA
A5	E1	N	SLA	SLA	N	SLA	A	SLA	A	A	SLD	A	SLA	A	N	A
	E2	A	A	A	A	A	A	SLA	A	A	SLA	SLA	A	D	SLA	A
	E3	SA	SA	SA	SA	A	SA	SLD	A	A	A	N	SA	SD	A	SA
	E4	SA	SA	SA	SA	SA	SA	SA	SLA	SA	N	SA	SLA	SLA	SA	A

Table 4. Ratings on criterions given by the decision panel

Experts	Criterion														
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
E1	VR	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER
E2	MR	MR	MR	MR	MR	VR	MR	MR	MR	N	MR	MR	N	N	N
E3	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER
E4	ER	ER	ER	ER	ER	ER	VR	MR	MR	MR	MR	ER	MR	ER	ER

Table 5. Linguistic term, HYFS, and scores for alternatives ratings data

Linguistic Term	HYFS	HYFS Score
Strongly Disagree (SD)	(0.1, 0.95)	0.105
Disagree (D)	(0.2, 0.9)	0.220
Slightly Disagree (SLD)	(0.3, 0.8)	0.360
Neutral (N)	(0.5, 0.5)	0.750
Slightly Agree (SLA)	(0.85, 0.3)	1.445
Agree (A)	(0.9, 0.2)	1.620
Strongly Agree (SA)	(0.95, 0.1)	1.805

Table 6. Linguistic term, HYFS, and scores for criterions ratings data

Linguistic Term	HYFS	Score
Not Relevant (NR)	(0.1, 0.95)	0.105
Slightly Relevant (SLR)	(0.2, 0.9)	0.220
Somewhat Relevant (SR)	(0.3, 0.8)	0.360
Neutral (N)	(0.5, 0.5)	0.750
Moderately Relevant (MR)	(0.85, 0.3)	1.445
Very Relevant (VR)	(0.9, 0.2)	1.620
Extremely Relevant (ER)	(0.95, 0.1)	1.805

Step b: The procedure described in Section 3.2 is to be applied on the CSPs rating data to find the weights for each expert. A summary of the results obtained by applying the procedure is given in Table 7. Table 7 contains variance in ratings of each CSPs, the sum of the variances for each expert, and the expert weights obtained.

Table 7. Expert weights computation

Experts	CSPs	Variance	Total Variance	Expert weights
E1	A1	0.177	0.898	0.265
	A2	0.191		
	A3	0.178		
	A4	0.184		
	A5	0.167		
E2	A1	0.077	0.523	0.155
	A2	0.142		
	A3	0.077		
	A4	0.107		
	A5	0.119		
E3	A1	0.318	1.508	0.446
	A2	0.301		
	A3	0.294		
	A4	0.294		
	A5	0.301		
E4	A1	0.070	0.452	0.134
	A2	0.074		
	A3	0.110		
	A4	0.119		
	A5	0.078		

Step c: The procedure described in Section 3.3 is to be applied on the criterion rating data to find the weights for each criterion. The normalized decision matrix for criterion weights computation obtained as an intermediary result is described in Table 8. The criteria weights obtained are shown in Table 9.

Step d: The procedure described in Section 3.4 is to be applied on the CSPs rating data to find the ranking for each CSPs. The rank values for each CSPs as computed for each individual expert is given in Table 10. The CSPs rankings determined using data given by each individual expert is given in Table 11.

The fusion procedure mentioned in the Section 3.4 is applied to obtain the final rankings of the CSPs. Table 12 describes the fusion procedure, beginning with the calculated values of $rs_i^{(e)} \cdot WK^{(e)}$ for all i^{th} alternatives, followed by computation of ars_i and $iars_i$, which is then used to find the final rankings of the CSPs. The final ranking of CSPs obtained is as follows:

A1 > A5 > A2 > A4 > A3.

4.3. Sensitivity analysis

In this section the impact of changes in criterion weights on rankings of the CSPs is explored. The criterion weights obtained in step c (Section 4.2) is modified systematically by increasing and decreasing the weights by a factor of 10% independently of each other. Doing this, 30 new sets of criterion weights are obtained, which are then used in the procedure mentioned in step d (Section 4.2), to determine $iars_i$ (mentioned in Section 3.4) of the CSPs.

Figure 2 and Figure 3 depict the impact of changing criterion weights on $iars_i$ values of the CSPs. It can be noted from the figures that the final rankings computed using $iars_i$, regardless of the sensitivity analysis scenarios, remain unchanged (that is A1 > A5 > A2 > A4 > A3), even though $iars_i$ itself has minor fluctuations. In the figures, the Y-axis denotes the $iars_i$ values computed for a specified CSP, and the X-axis labels denote the criterion in whose weight the change has been made.

5. Discussion and conclusions

The selection of a CSP is a major decision in the lifecycle of any infrastructure project, carrying significant implications for project success, quality, and cost-effectiveness. Traditional procurement processes, often prioritizing the lowest bid, have shown to be inadequate in ensuring optimal outcomes, frequently leading to compromised project quality, delays, and even failures.

This study, recognizing the need for more robust and holistic evaluation frameworks, introduces an integrated decision-making approach for assessing CSPs. The study addresses limitations identified in the existing MCDM approaches within the construction industry. The framework proposed in the study also uniquely combines HYFS to manage uncertainty in expert opinions, the variance method for determining expert weights, the LOPCOW for criterion weighting, and the WASPAS for ranking CSPs.

Table 8. Normalized decision matrix for criterion weights computation

Experts	Criterion														
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
	Benefit	Benefit	Benefit	Benefit	Benefit	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Benefit	Cost	Benefit	Benefit
E1	0.486	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	1.000	1.000	0.000	1.000	1.000
E2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
E3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	1.000	1.000	0.000	1.000	1.000
E4	1.000	1.000	1.000	1.000	1.000	1.000	0.486	0.000	0.000	0.341	0.000	1.000	0.341	1.000	1.000

Table 9. Criterion weights computation

Criterion	$\sqrt{\frac{\sum_{e=1}^{k}\left(g_j^{(e)}\right)^2}{k}}$	σ_j	P_j	WC_j
C1	0.7477	0.4157	58.7135	0.0710
C2	0.8660	0.4330	69.3147	0.0838
C3	0.8660	0.4330	69.3147	0.0838
C4	0.8660	0.4330	69.3147	0.0838
C5	0.8660	0.4330	69.3147	0.0838
C6	0.8660	0.4330	69.3147	0.0838
C7	0.7477	0.4157	58.7135	0.0710
C8	0.7071	0.5000	34.6574	0.0419
C9	0.7071	0.5000	34.6574	0.0419
C10	0.5283	0.4083	25.7770	0.0312
C11	0.7071	0.5000	34.6574	0.0419
C12	0.8660	0.4330	69.3147	0.0838
C13	0.5283	0.4083	25.7770	0.0312
C14	0.8660	0.4330	69.3147	0.0838
C15	0.8660	0.4330	69.3147	0.0838

Table 10. Rank values of CSPs

Experts	A1	A2	A3	A4	A5
E1	1.0000	0.9455	0.9275	0.9351	0.9829
E2	0.5418	0.9824	0.5248	0.5572	0.9224
E3	1.0000	0.9781	0.9694	0.9694	0.9781
E4	0.9348	0.9239	0.8322	0.8579	0.9372

Table 11. Individual expert ranking of CSPs

Experts	A1	A2	A3	A4	A5
E1	1	3	5	4	2
E2	4	1	5	3	2
E3	1	2	3	3	2
E4	2	3	5	4	1

Table 12. Rank fusion to obtain the final ranking of CSPs

Experts	A1 $rs_1^{(e)} \cdot WK^{(e)}$	A2 $rs_2^{(e)} \cdot WK^{(e)}$	A3 $rs_3^{(e)} \cdot WK^{(e)}$	A4 $rs_4^{(e)} \cdot WK^{(e)}$	A5 $rs_5^{(e)} \cdot WK^{(e)}$
E1	0.265	0.795	1.325	1.06	0.53
E2	0.62	0.155	0.775	0.465	0.31
E3	0.446	0.892	1.338	1.338	0.892
E4	0.268	0.402	0.67	0.536	0.134
Procedure to obtain the final ranks					
ars_i	1.599	2.244	4.108	3.399	1.866
$iars_i$	2.509	1.864	0	0.709	2.242
Rank	1	3	5	4	2

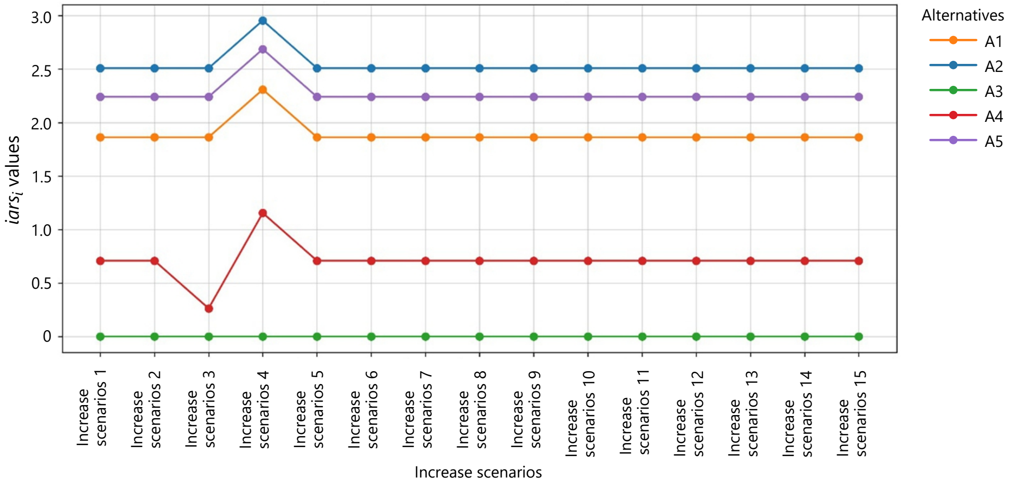

Figure 2. Sensitivity analysis (increase by factor 10%) on $iars_i$ by modifying the criterion weights

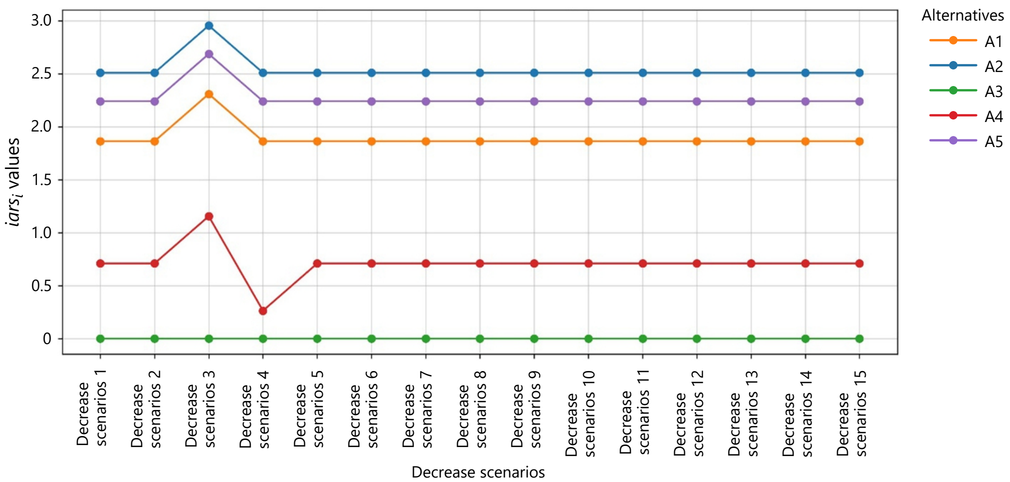

Figure 3. Sensitivity analysis (decrease by factor 10%) on $iars_i$ by modifying the criterion weights

By integrating these components, the proposed framework supports the shift from traditional cost-centric bidding methods towards a more robust and balanced approach to CSP selection.

It was noted that in the existing literature for construction industry, the frameworks adopted traditional fuzzy set methods, such as TFNs and interval-valued fuzzy for modelling uncertainty. Therefore, the use of HYFS in the study is a significant difference when compared to existing literature. HYFS, by using product-based constraint rather than the sum-based constraint of membership and non-membership degrees, provides more flexibility to model uncertainties present in expert judgments. Further, unlike in existing studies, the presented method incorporates the weights of the experts in the decision process. By assigning weights based on the variance in their evaluations, the framework acknowledges the differing levels of reliability among decision-makers. This mitigates the risk of biased or skewed outcomes that may result when all expert given data are treated equally. The LOPCOW method for calculating criterion weights also offers a balanced perspective. Unlike traditional methods that may lead to skewed weighting, LOPCOW effectively captures the extreme values and their importance using a logarithmic operator. This ensures that all criteria, from project experience to environmental impact, are appropriately weighted according to their relative importance. The framework proposed and the case application of the framework in the study is compared with few other frameworks used in the extant literature in Table 13.

The application of the framework to the case study in India demonstrated its practical utility in selecting an optimal CSP. The ranking of CSPs obtained through the framework A1 > A5 > A2 > A4 > A3 provides a clear ordering of the alternatives that consider both qualitative and quantitative criteria. The weights of the criterions obtained revealed that Years of experience (C2), Reputation (C3), Project success rate (C4), Compliance with standards (C5), Material quality (C6), Good impacts (C12), Specialized project handling capability (C14), and Innovation (C15) are the criterions that have been considered as the most important criterions by the decision panel of the study.

Table 13. Comparative analysis of the study with studies from extant literature

Features	Proposed framework	Long (2025)	Nithya et al. (2024)	Fawzy et al. (2024)
Case application	Indian based CSP selection	Contractor selection for heritage building renovations	Dual phase contractor selection for construction projects	Egyptian road maintenance contractor selection
Number of criterions considered	15	12	6	7
Framework summary	HYFS-Variance-LOPCOW-WASPAS	TFN-BWM-TOPSIS	IVFS-DWMCDM	AHP-TOPSIS-VIKOR
Fuzzy used	HYFS	TFN	IVFS	None
Expert weight modelled	Yes	No	No	No
Individual expert personalized ranks of alternatives provided	Yes	No	No	No
Criterion weights considered	Yes	Yes	Yes	Yes
Extremities in data for criterion weights computation considered	Yes	No	No	No

The sensitivity analysis performed in the study further validates the robustness of the framework. Despite systematically altering the criterion weights by increasing and decreasing it by 10% for each criterion, the final rankings remain consistent, indicating that the framework is resilient to changes in the relative importance of criteria.

In conclusion the study contributes to the extant literature by:

1. This study introduces the application of HYFS to the CSP selection problem, offering a more flexible approach to modelling uncertainty compared to traditional fuzzy methods like TFNs or IVFS commonly used in the literature.
2. Unlike many existing MCDM frameworks for CSP selection, this study explicitly incorporates expert weights based on the variance in their evaluations. This acknowledges the differing levels of expertise and reliability among decision-makers, thus providing a more realistic and less biased approach to multi-expert decision-making.
3. The study uses LOPCOW for determining criterion weights for CSP selection problem, which provides a more balanced allocation and is capable to handling extremities in the expert given data compared to other weighting techniques.
4. The study proposed an integrated HYFS, Variance, LOPCOW, and WASPAS decision making framework for selection problems.

Some implications of the study are:

1. The proposed decision system is a supplementary system that facilitates decision-making by considering data driven methods for arriving at a specific decision.
2. The integrated approach serves as a tool for making rational decisions that supports stakeholders with a mathematical rigor that enables back tracking, which not possible during intuitive process.
3. The presented decision tool can serve in a bi-directional manner allowing customers and construction service providers clarity on different measures and metrics for improvement and better understand competitors during the process – this significantly helps in the growth of construction industries by properly understanding the pain points and taking corrective measures to improve.
4. Some level of training is required to effectively use the presented system, which can be obtained via hands-on sessions and mock training with case examples, so that stakeholders can get effective benefit from the proposal.
5. The implicit uncertainty that exists within the decision process is better handled by this decision system by allowing expression of thoughts as a orthopair with flexibility to express the degree of preference and non-preference, which is lacking in other variants of orthopair forms.

Some limitations of the study exist, despite the merits:

1. A priori information about entities cannot be accepted/considered during rank determination by the proposed system.
2. Data is assumed to be complete and missing data/rating is not acceptable input for the system.
3. Finally, the decision that emanates from the system is based on data from experts, which is sort of pilot case, which at present cannot expand to social media handles to fetch data via crawlers to taking decision at real-time.

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Author contributions

Abhishek Yadav was responsible for conceptualization, data curation, formal analysis, methodology, software, and writing – original draft; Raghunathan Krishankumar was responsible for conceptualization, formal analysis, methodology, software, and writing – original draft; Kattur Soundarapandian Ravichandran was responsible for formal analysis, methodology, prototype development, investigation, and writing – original draft; Jurgita Antucheviciene was responsible for methodology, data curation, investigation, review, and writing – original draft; Edmundas Kazimieras Zavadskas was responsible for methodology, data curation, investigation, review, writing – original draft, and supervision.

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References

Alamoodi, A., Garfan, S., Deveci, M., Albahri, O. S., Albahri, A. S., Yussof, S., Homod, R. Z., Sharaf, I. M., & Moslem, S. (2024). Evaluating agriculture 4.0 decision support systems based on hyperbolic fuzzy-weighted zero-inconsistency combined with combinative distance-based assessment. *Computers and Electronics in Agriculture*, *227*, Article 109618. https://doi.org/10.1016/j.compag.2024.109618

Anysz, H., Nicał, A., Stević, Ž., Grzegorzewski, M., & Sikora, K. (2021). Pareto optimal decisions in multi-criteria decision making explained with construction cost cases. *Symmetry*, *13*(1), Article 46. https://doi.org/10.3390/sym13010046

Aydin, N., Seker, S., & Özkan, B. (2022). Planning location of mobility hub for sustainable urban mobility. *Sustainable Cities and Society*, *81*, Article 103843. https://doi.org/10.1016/j.scs.2022.103843

Alkhateeb, A. M., Hyari, K. H., & Hiyassat, M. A. (2021). 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

Chen, Z. S., Zhang, X., Rodríguez, R. M., Pedrycz, W., & Martínez, L. (2021). Expertise-based bid evaluation for construction-contractor selection with generalized comparative linguistic ELECTRE III. *Automation in Construction*, *125*, Article 103578. https://doi.org/10.1016/j.autcon.2021.103578

Deepika, S., Anandakumar, S., Bhuvanesh Kumar, M., & Baskar, C. (2023). Performance appraisement of supplier selection in construction company with Fuzzy AHP, Fuzzy TOPSIS, and DEA: A case study based approach. *Journal of Intelligent* & *Fuzzy Systems*, *45*(6), 10515–10528. https://doi.org/10.3233/JIFS-231790

Dhumras, H., & Bajaj, R. K. (2024). On potential strategic framework for green supply chain management in the energy sector using q-rung picture fuzzy AHP & WASPAS decision-making model. *Expert Systems with Applications*, *237*, Article 121550. https://doi.org/10.1016/j.eswa.2023.121550

Dutta, P., & Borah, G. (2023). Construction of hyperbolic fuzzy set and its applications in diverse COVID-19 associated problems. *New Mathematics and Natural Computation*, *19*(1), 217–288. https://doi.org/10.1142/S1793005723500072

Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. *Omega*, *112*, Article 102690. https://doi.org/10.1016/j.omega.2022.102690

Ecer, F., Küçükönder, H., Kaya, S. K., & Görçün, Ö. F. (2023). Sustainability performance analysis of micro-mobility solutions in urban transportation with a novel IVFNN-Delphi-LOPCOW-CoCoSo framework. *Transportation Research Part A*: *Policy and Practice*, *172*, Article 103667. https://doi.org/10.1016/j.tra.2023.103667

Ellis, J., Edwards, D. J., Thwala, W. D., Ejohwomu, O., Ameyaw, E. E., & Shelbourn, M. (2021). A case study of a negotiated tender within a small-to-medium construction contractor: modelling project cost variance. *Buildings*, *11*(6), Article 260. https://doi.org/10.3390/buildings11060260

Fawzy, M. M., Elsharkawy, A. S., Khalifa, Y. A., & Hassan, A. A. (2024). Contractor selection by using multi-criteria decision-making for Egyptian road maintenance. *International Journal of System Assurance Engineering and Management*, *15*(6), 2351–2365. https://doi.org/10.1007/s13198-024-02249-3

Ferrans, P., Torres, M. N., Temprano, J., & Sánchez, J. P. R. (2022). Sustainable Urban Drainage System (SUDS) modeling supporting decision-making: A systematic quantitative review. *Science of the Total Environment*, *806*(Part 2), Article 150447. https://doi.org/10.1016/j.scitotenv.2021.150447

Ghafoori, M., & Abdallah, M. (2024). Multi-criteria decision support model for material and supplier selection in the construction industry. *International Journal of Construction Management*, *25*(4), 409–418. https://doi.org/10.1080/15623599.2024.2327251

Ghorbani, S., Bour, K., & Javdan, R. (2025). Applying the PROMETHEE II, WASPAS, and CoCoSo models for assessment of geotechnical hazards in TBM tunneling. *Scientific Reports*, *15*(1), Article 491. https://doi.org/10.1038/s41598-024-84826-x

Görçün, Ö. F., Pamucar, D., & Küçükönder, H. (2024). Selection of tramcars for sustainable urban transportation by using the modified WASPAS approach based on Heronian operators. *Applied Soft Computing*, *151*, Article 111127. https://doi.org/10.1016/j.asoc.2023.111127

Guo, Z., Liu, J., Liu, X., Meng, Z., Pu, M., Wu, H., Yan, X., Yang, G., Zhang, X., Chen, C., & Chen, F. (2024). An integrated MCDM model with enhanced decision support in transport safety using machine learning optimization. *Knowledge-Based Systems*, *301*, Article 112286. https://doi.org/10.1016/j.knosys.2024.112286

Hakimi, M., Daneshvar, A., Ehsanifar, M., & Nouri, I. (2024). Applying Fuzzy Utilities Additives STAR for sustainable supplier selection in Iran's construction industry. *International Journal of Engineering*, *37*(10), 2008–2020. https://doi.org/10.5829/IJE.2024.37.10A.12

Hallak, J. (2024). Optimizing construction supplier selection in conflict-affected regions: a hybrid multi-criteria framework. *Operations Management Research*, *17*, 1270–1294. https://doi.org/10.1007/s12063-024-00505-0

Hanák, T., Drozdová, A., & Marović, I. (2021). Bidding strategy in construction public procurement: A contractor's perspective. *Buildings*, *11*(2), Article 47. https://doi.org/10.3390/buildings11020047

Jagadeeswari, M., & GomathiNayagam, V. L. (2017). Approximation of parabolic fuzzy numbers. In *Frontiers in artificial intelligence and applications*. *Vol. 299*: *Fuzzy systems and data mining III* (pp. 107–124). IOS Press. https://doi.org/10.3233/978-1-61499-828-0-107

Ji, L., Zhang, D., Wang, Z., Liu, M., Sun, M., Zhang, H., Kraiem, N., & Anjum, M. (2025). Paradigm shift in implementing smart technologies for machinery optimisation in manufacturing using decision support system. *Alexandria Engineering Journal*, *114*, 526–542. https://doi.org/10.1016/j.aej.2024.11.106

Kiani Mavi, N., Brown, K., Fulford, R. G., & Goh, M. (2025). An MCDM analysis of critical success criteria for medium and large construction projects in Australia and New Zealand. *Engineering*, *Construction and Architectural Management*, *32*(8), 5160–5193. https://doi.org/10.1108/ECAM-08-2023-0838

Kishore, R., Dehmourdi, S. A. M., Naik, M. G., & Hassanpour, M. (2020). Designing a framework for Subcontractor's selection in construction projects using MCDM model. *Operational Research in Engineering Sciences*: *Theory and Applications*, *3*(3), 48–64. https://doi.org/10.31181/oresta20303048k

Korucuk, S., Aytekin, A., Görçün, Ö., Simic, V., & Görçün, Ö. F. (2024). Warehouse site selection for humanitarian relief organizations using an interval-valued fermatean fuzzy LOPCOW-RAFSI model. *Computers* & *Industrial Engineering*, *192*, Article 110160. https://doi.org/10.1016/j.cie.2024.110160

Long, L. D. (2025). Integrating the group-based fuzzy best-worst method and fuzzy technique for order of preference by similarity to ideal solution for selecting contractors for heritage building renovation projects. *Engineering Applications of Artificial Intelligence*, *142*, Article 109928. https://doi.org/10.1016/j.engappai.2024.109928

López, L. M., Ishizaka, A., Qin, J., & Carrillo, P. A. (2023). *Multi-criteria decision-making sorting methods*: *Applications to real-world problems*. Academic Press.

Masoomi, B., Sahebi, I. G., Fathi, M., Yıldırım, F., & Ghorbani, S. (2022). Strategic supplier selection for renewable energy supply chain under green capabilities (fuzzy BWM-WASPAS-COPRAS approach). *Energy Strategy Reviews*, *40*, Article 100815. https://doi.org/10.1016/j.esr.2022.100815

Mohandes, S. R., Sadeghi, H., Mahdiyar, A., Durdyev, S., Banaitis, A., Yahya, K., & Ismail, S. (2020). Assessing construction labours' safety level: A fuzzy MCDM approach. *Journal of Civil Engineering and Management*, *26*(2), 175–188. https://doi.org/10.3846/jcem.2020.11926

Naz, S., Shafiq, A., Butt, S. A., Tasneem, R., Pamucar, D., & Gonzalez, Z. C. (2025). Decision-making model for selecting products through online product reviews utilizing natural language processing techniques. *Neurocomputing*, *611*, Article 128593. https://doi.org/10.1016/j.neucom.2024.128593

Von Neumann, J., & Morgenstern, O. (2007). *Theory of games and economic behavior* (*60th anniversary commemorative edition*). Princeton University Press. https://doi.org/10.1515/9781400829460

Nila, B., & Roy, J. (2023). A new hybrid MCDM framework for third-party logistics provider selection under sustainability perspectives. *Expert Systems with Applications*, *234*, Article 121009. https://doi.org/10.1016/j.eswa.2023.121009

Nithya, N. S., Thota, S., Rathour, L., & Shanmugasundaram, P. (2024). A new multi-criteria decision making method for the selection of construction contractors using interval valued fuzzy set. *BMC Research Notes*, *17*(1), Article 113. https://doi.org/10.1186/s13104-024-06769-w

Rong, Y., Yu, L., Liu, Y., Simic, V., & Garg, H. (2024). The FMEA model based on LOPCOW-ARAS methods with interval-valued Fermatean fuzzy information for risk assessment of R&D projects in industrial robot offline programming systems. *Computational and Applied Mathematics*, *43*(1), Article 25. https://doi.org/10.1007/s40314-023-02532-2

Santos, P. A. S., Cortez, B., & Carvalho, M. T. M. (2025). Integrating GIS and BIM with MCDM for infrastructure planning: A comprehensive framework. *Engineering*, *Construction and Architectural Management*, *32*(6), 4197–4226. https://doi.org/10.1108/ECAM-08-2023-0830

Shume, H. A., & Mitikie, B. B. (2024). An integrated Delphi and Fuzzy AHP model for contractor selection: a case of Addis Ababa Design and Construction Works Bureau. *Cogent Engineering*, *11*(1), Article 2357724. https://doi.org/10.1080/23311916.2024.2357724

Simic, V., Dabic-Miletic, S., Tirkolaee, E. B., Stević, Ž., Ala, A., & Amirteimoori, A. (2023). Neutrosophic LOPCOW-ARAS model for prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems. *Applied Soft Computing*, *143*, Article 110400. https://doi.org/10.1016/j.asoc.2023.110400

Ulutaş, A., Balo, F., & Topal, A. (2023). Identifying the most efficient natural fibre for common commercial building insulation materials with an integrated PSI, MEREC, LOPCOW and MCRAT model. *Polymers*, *15*(6), Article 1500. https://doi.org/10.3390/polym15061500

Ulutaş, A., Topal, A., Görçün, Ö. F., & Ecer, F. (2024). Evaluation of third-party logistics service providers for car manufacturing firms using a novel integrated grey LOPCOW-PSI-MACONT model. *Expert Systems with Applications*, *241*, Article 122680. https://doi.org/10.1016/j.eswa.2023.122680

Wang, K., Ying, Z., Goswami, S. S., Yin, Y., & Zhao, Y. (2023). Investigating the role of artificial intelligence technologies in the construction industry using a Delphi-ANP-TOPSIS hybrid MCDM concept under a fuzzy environment. *Sustainability*, *15*(15), Article 11848. https://doi.org/10.3390/su151511848

Zavadskas, E. K., Turskis, Z., Antucheviciene, J., & Zakarevicius, A. (2012). Optimization of weighted aggregated sum product assessment. *Elektronika ir elektrotechnika*, *122*(6), 3–6. https://doi.org/10.5755/j01.eee.122.6.1810

Zavadskas, E. K., Krishankumar, R., Ravichandran, K. S., Vilkonis, A., & Antucheviciene, J. (2025). Hyperbolic fuzzy set decision framework for construction contracts integrating CRITIC and WASPAS for dispute mitigation. *Automation in Construction*, *174*, Article 106137. https://doi.org/10.1016/j.autcon.2025.106137