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GRADING GREEN BUILDING MATERIALS: A HYPERBOLIC FUZZY FRAMEWORK FOR A SUSTAINABLE HOSPITAL

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Abstract. Sustainable hospitals require careful selection of green building materials (GBMs) to reduce eco-impact and improve resilience. This is crucial as hospitals consume significant resources and their material choices influence durability, availability, and indoor air quality. Existing studies did not model uncertainty effectively, calculate experts' weights methodically, and determine personalized/combined ranks of GBMs. This paper aims to address these gaps by developing an integrated decision framework that evaluates factors/criteria, assigns importance values, and ranks GBMs systematically. The methodology combines hyperbolic fuzzy data with attitudinal variance, LOPCOW, and choice-based WISP methods to determine experts' weights, factor importance, and material grades. The proposed rank algorithm produces both personalized and cumulative grades. Results show durability, material availability, and indoor air quality as the top three factors, with hempcrete, cross-laminated timber, and rammed earth as the leading GBMs. This framework contributes by offering stakeholders a rational, uncertainty-resilient tool for sustainable hospital design.

Keywords: hyperbolic fuzzy set, green building materials, WISP method, LOPCOW method, sustainable buildings.

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Notations

Abbreviations

GBM – Green Building Material
LOPCOW – LOgarithmic Percentage Change-driven Objective Weighting
WISP – Integrated Simple Weighted Sum Product Method
MADM – Multi-Attribute Decision-Making
HyFS – Hyperbolic Fuzzy Set
AHP – Analytic Hierarchy Process
TOPSIS – Technique for Order of Preference by Similarity to Ideal Solution
MULTIMOORA – Multi-Objective Optimization on the basis of a Ratio Analysis plus the full MULTIplicative form
DEMATEL – Decision Making Trial and Evaluation Laboratory
ANP – Analytic Network Process
COPRAS – Complex Proportional Assessment
ARAS – Additive Ratio Assessment
CRITIC – CRiteria Importance Through Intercriteria Correlation
MEREC – MEthod based on the Removal Effects of Criteria
CoCoSo – Combined Compromise Solution
SWARA – Stepwise Weight Assessment Ratio Analysis
CODAS – COmbinative Distance-based ASsessment
VIKOR – VIekriterijumsko KOmpromisno Rangiranje
OPTBIAS – Ordering Preference Targeting at Bi-Ideal Average Solutions
BMW – Best Worst Method
RANCOM – RANking COMparison
PIPRECIA – Pairwise RElative Criteria Importance Assessment

1. Introduction

Health 4.0 places a strong emphasis on green and sustainable practices – from building infrastructure to renovating it, managing waste, and integrating technology (Monteiro et al., 2018; Faggini et al., 2018). The construction industry, however, has long been criticized for its harmful environmental impact, particularly emissions of hazardous substances (Tunji-Olayeni et al., 2019). A report from the

Times of India (2022) revealed that nearly 50% of climate change and landfill, 23% of air pollution, and 40% of water pollution can be associated to construction activities. These findings highlight the urgency for advancements in sustainable construction practices to mitigate such detrimental effects on the planet and human health. Spūdys et al. (2025) presented a stakeholder level perspective of renovation criteria to better understand the views of construction experts and building owners – which showed disagreements leading to deacceleration of decarbonisation initiatives by countries. This study motivates and calls for a decision framework that could embed diverse stakeholders' perspectives and present decisions in a rational and scientific manner.

Sustainable construction has emerged as a promising solution to minimize eco-impact, optimize resource utilization, and enhance energy efficiency throughout the building lifecycle (Goodhew, 2016). Since materials form the foundation of any construction, researchers have emphasized that adopting green building materials (GBMs) significantly promotes sustainability (Mokal et al., 2015). In recent times, the availability of innovative green materials has expanded, and their selection has become complex due to competing/conflicting criteria. This complexity urges for rational decision-making that can balance multiple criteria effectively and select a logical alternative for the process.

Multi-attribute decision-making (MADM) enables evaluation and selection of GBMs for sustainable construction based on multiple criteria (Khoshnava et al., 2018). Bajwa et al. (2025) recently presented a detailed review of multi-criteria decision methods for material selection and clarified the importance and need for decision methods in rational selection of materials for sustainable construction. GBMs are crucial entity in sustainable construction, which focuses on reduced emissions of greenhouse gases and other toxic substances into the environment. Literature reveals that stakeholders such as university/government researchers, engineers, construction architects, material manufacturers develop/co-develop GBMs (Spiegel & Meadows, 2010) and the diverse collection of such GBMs with varying performance in different key indicators makes the selection process complex yet crucial. Structural materials are selected methodically by extending AHP-TOPSIS with entropy measure for supporting sustainability (Bakhoum & Brown, 2013). Zavadskas et al. (2017) extended MULTIMOORA method to neutrosophic context for grading residential house material. Zhang et al. (2017) considered different methods such as TOPSIS, DEMATEL, and alike for grading GBMs to support sustainability. Khoshnava et al. (2018) presented DEMATEL with ANP in the fuzzy context for the rational selection of GBMs by considering the three pillars of sustainability. Tian et al. (2018) proposed grey correlation measure for facilitating selection of GBMs towards interior decoration. Azahar et al. (2020) applied factor analysis to determine the weights of the GBMs for its suitability in pavement projects. Zindani et al. (2020) proposed aggregation multiplicative rule for facilitating rational material selection. Balali et al. (2020) applied SWARA and COPRAS for GBM selection to support the sustainable development goals. AHP method was applied for determining suitable attributes for GBM selection (Mayhoub et al., 2021). Sustainable materials are prioritized by integrating evidence theory with ARAS method (Hatefi et al., 2021). Viable zero-carbon material is chosen from the proposed q-rung orthopair CRITIC-COPRAS model (Krishankumar et al., 2022). Marinković et al. (2022) presented MEREC and CoCoSo combined framework for determining the mixtures' grades to support sustainability. Remadi and Frikha (2023) presented intuitionistic fuzzy-based CODAS model for GBM selection. The simple rank procedure was introduced, and it was applied for GBM selection by Zakeri et al. (2023).

Recently, work from Li et al. (2025) inferred that decision-making is crucial in the lifecycle GBM for effective implementation in construction. Cheng et al. (2025) also witnessed the usefulness of MADM to rational selection GBMs. Fan et al. (2025) applied MADM integrated methods for GBMs. Accordingly, this study addresses two key research questions: (RQ1) What factors/criteria are associated with GBM selection, and how can their relative importance be determined? (RQ2) What is the grade or rank of each GBM, and how can a priority order of materials be obtained for rational planning and management? These questions provide the foundation for developing a structured decision framework.

Despite prior contributions, certain research gaps still remain. First, uncertainty is not adequately modelled in existing approaches. Second, expert weights are often ignored or directly assigned, introducing bias and subjectivity. Third, extreme rating values or rating fluctuations can distort factor importance. Finally, current models lack the ability to generate personalized grading or ranking of GBMs. Addressing these gaps requires methodological innovations capable of balancing objectivity, flexibility, and personalization.

Motivated by these challenges, this study proposes an integrated framework that draws on multiple methods. The hyperbolic fuzzy set (HyFS) models uncertainty by incorporating membership and non-membership grades simultaneously. Attitudinal variance captures both risk-averse and risk-seeking characteristics to determine expert weights more objectively. The LOPCOW method is extended within the HyFS context to balance factor weights and reduce the influence of extreme ratings. Finally, the choice-based WISP procedure is adapted to enable personalized grading of GBMs, closely reflecting human cognition in ranking decisions.

The rationale for these contributions is threefold. First, HyFS (Dutta & Borah, 2023) provides an orthopair structure that allows flexible interpretation of qualitative ratings without rigid restrictions. Second, the combination of attitudinal variance and LOPCOW (Ecer & Pamucar, 2022) ensures systematic determination of expert and factor weights, minimizing subjectivity while addressing the impact of extreme values. Third, the WISP method (Stanujkic et al., 2021), enhanced with personal choice vectors, enables personalized grading and ranking of GBMs using a simple, transparent procedure. Together, these methods establish a rational and uncertainty-resilient decision-making framework.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature, Section 3 details the proposed research methodology, Section 4 demonstrates the methodology on a GBM selection case for sustainable floor/wall construction. Section 5 discusses the sensitivity and comparison analysis and Section 6 concludes with summarising key findings, limitations and future research paths.

2. Literature review

2.1. Sustainable hospitals

Recent studies show that sustainable hospitals represent holistic strategies to address the triple challenge of environmental protection, fiscal responsibility, and patient well-being. Hospitals employing renewable energy systems (solar, wind, geothermal), passive architectural orientation, and smart automation have demonstrated reductions in operational emissions and utility costs over the long-term (Silva et al., 2024; Schwab et al., 2025). Their design leverages recycled, local, or low-carbon materials, green roofs, robust insulation, and natural ventilation—features directly linked to facility longevity and ecological stewardship (Brambilla et al., 2024; Alsawaf & Albadry, 2022).

Implementation of biodegradable/reusable medical supplies, waste segregation, and circular economy principles positions operating rooms and high-waste departments as sites of major intervention (Olawade et al., 2025). Furthermore, such hospitals achieve greater efficiency through digital patient records, telemedicine, and intelligent resource management, reducing unnecessary travel and paperwork (Brambilla et al., 2024; Padget et al., 2024).

Socially, sustainable hospitals promote local economic development via regional procurement, and improve health outcomes through safer environments and sustainable food systems (Schwab et al., 2025; Hussain et al., 2024). As global health systems pivot toward climate accountability and resource stewardship, adopting these multifaceted sustainable practices is critical for resilient, cost-effective, and healing-oriented care.

2.2. Green building materials

Green building materials (GBMs) have emerged as essential components in sustainable construction, offering significant environmental and health benefits (Allen et al., 2015). Recent literature highlights that GBMs reduce energy consumption, resource use, and indoor pollutants, fostering healthier building environments (Ekhaese & Ndimako, 2023). Innovations in the use of natural fibers, recycled products, and composites are transforming building practices, despite some challenges regarding durability and market adaptation (Firoozi et al., 2024). The integration of GBMs in healthcare and hospital design has received particular attention, with sustainable hospitals achieving decreased operational costs, lower patient mortality, and improved recovery times (Vallée, 2024). These facilities prioritize renewable energy adoption, waste reduction, and the use of local, non-toxic materials to minimize environmental footprints (Tarkar, 2022). However, regulatory, financial, and operational barriers persist, requiring holistic strategies and green leadership for successful implementation in healthcare (Berniak-Woźny & Rataj, 2023). The cumulative research suggests that GBMs are central to advancing sustainability goals and creating resilient, healthy environments in both general and specialized settings such as hospitals.

2.3. LOPCOW and WISP

The extant literature on the decision models used in the proposed framework are reviewed here:

LOPCOW (Ecer & Pamucar, 2022) is a popular objective weight calculation method that considers variability and applies log operation for balancing spikes. Bektas (2022) assessed the insurance sector of Turkey by using different methods including LOPCOW, EDAS, and alike. Simic et al. (2023) evaluated warehouse system for its smartness and sustainability by extending LOPCOW to neutrosophic context. Ecer et al. (2023a, 2023b) developed an interval variant neutrosophic-based model with CoCoSo and LOPCOW for micromobility sustainability evaluation. Drones for agriculture process were chosen by extending LOPCOW and VIKOR to generalized orthopair forms. Countries performance in terms of sustainable development is assessed by combined PIV and LOPCOW methods. Suitable insulation material is selected that is natural fibre by applying diverse decision methods like MEREC, LOPCOW, and others. Dhruva et al. (2024) applied the Fermatean fuzzy-based LOPCOW-CoCoSo combination for cloud vendor grading within healthcare sector. An integrated LOPCOW and OPTBIAS combination is used for robot selection within the manufacturing context (Chatterjee et al., 2024). Nişel and Nişel (2024) presented countries innovation metric by extending LOPCOW and CoCoSo methods. Turkish universities are analyzed for their performance by extending LOPCOW and CRADIS methods (Dündar, 2024). Yasin et al. (2025) put forward a hybrid model by considering machine learning, LOPCOW, and Einstein Choquet integral function for assessing solid waste management under the fuzzy context.

WISP is a simple and elegant rank method for determining the priority of alternatives (Stanujkic et al., 2021). Theoretical aspects are strengthened via comparison of different normalization operator for WISP (Zavadskas et al., 2022a). Ulutaş et al. (2022a) came up with the MEREC and WISP combination for pallet truck prioritization. Karabsevic et al. (2022) gave an extension of WISP to triangular fuzzy context. Stanujkic et al. (2022) extended WISP approach to neutrosophic set for evaluating rural tourist. Intuitionistic fuzzy WISP approach is proposed for contractor selection by Zavadskas et al. (2022b). Ulutaş et al. (2022b) extended WISP and BWM combination under grey number for grading sustainable suppliers. Kirmizi et al. (2023) applied integer linear programming with WISP and TOPSIS for prioritizing naval ship drainage systems. Recently, Rani et al. (2024a) selected an appropriate location for setting up wind power station within the context of interval variant of intuitionistic fuzzy RANCOM and WISP combination. Micromobility risk management options are graded via WISP metho under the interval variant of intuitionistic fuzzy context (Rani et al., 2024b). Görçün et al. (2024) presented a hybrid PIPRECIA and WISP combination with interval variant of Fermatean fuzzy number for ranking telescopic forklift. An integrated AHP-WISP framework is presented for aircraft carrier selection in Brazil (Diniz et al., 2024). Cao et al. (2024) extended WISP to rough numbers for aiding in determination of optimal ERP software for different sectors.

2.4. Insights from review

From the review of extant studies in GBM, it is inferred that there are some research gaps in the selection of suitable GBM from a set of GBMs based on certain key criteria/attributes. As a result, decision-making becomes a potential tool for facilitating the selection process. Previous studies show some research gaps, which are summarized in Table 1. This table serves as a motivation for this paper and enables authors to propose a novel integrated decision model that circumvents these challenges/gaps.

Table 1. Research gap summary in green material selection context

Sources	Uncertainty handling	Experts' weights	Personalized ranking
Bakhoum and Brown (2013)	Weak	No	No
Zavadskas et al. (2017)	Weak	No	No
Zhang et al. (2017)	Weak	No	No
Khoshnava et al. (2018)	Weak	No	No
Tian et al. (2018)	Weak	No	No
Azahar et al. (2020)	Weak	No	No
Zindani et al. (2020)	Weak	No	No
Balali et al. (2020)	Weak	No	No
Hatefi et al. (2021)	Weak	No	No
Krishankumar et al. (2022)	Strong	No	No
Fan et al. (2025)	Strong	No	No
Cheng et al. (2025)	Weak	No	No

Note: Weak is used to represent the lack of orthopair format to interpret uncertainty.

3. Research methods

The methods used in this study are described in this section.

3.1. Preliminaries

Definition 1 (Yager, 2016): P is a reference set. "q-Rung orthopair fuzzy set (q-ROFS)" Q on P is given by,

$$Q = \left(p, \mu_Q\left(p\right), \upsilon_Q\left(p\right) \mid p \in P\right), \tag{1}$$

where: $\mu_Q\left(p\right)$ is the membership grade; $\upsilon_Q\left(p\right)$ is the non-membership grade.

The grades follow the inequality – $0 \le \mu_Q^q + \upsilon_Q^q \le 1$ with $q \ge 1$.

Definition 2 (Dutta & Borah, 2023): P is a reference set. HyFS E on P is given by,

$$E = \left(p, \mu_E\left(p\right), \upsilon_E\left(p\right) \mid p \in P\right), \tag{2}$$

where the grades are in the unit interval and $\mu_E\left(p\right) \cdot \upsilon_E\left(p\right) \le 1$.

Note: $E_i = \left(\mu_i, \upsilon_i\right) \forall i = 1, 2, \ldots.$ is the hyperbolic fuzzy number (HyFN) and such numbers together from HyFS.

Definition 3 (Dutta & Borah, 2023; Divsalar et al., 2023): Let E_1 and E_2 be two HyFNs. Comparison methods are given by,

$$S\left(E_1\right) = 2\mu_1 - \mu_1\upsilon_1; \tag{3}$$

$$A\left(E_1\right) = 2\upsilon_1 - \mu_1\upsilon_1. \tag{4}$$

If $S\left(H_1\right) > S\left(H_2\right)$ then $E_1 > E_2$;

If $S\left(E_1\right) = S\left(E_2\right)$ then check if $A\left(E_1\right) > A\left(E_2\right)$ then $H_2 > H_1$;

If $A\left(E_1\right) = A\left(E_2\right)$ then $E_1 = E_2$.

Eqs. (3)–(4) is the score and accuracy measure.

Definition 4 (Dutta & Borah, 2023; Divsalar et al., 2023): E_1 and E_2 are two HyFNs. Some operations are given by,

$$E_1 \oplus E_2 = \left(\mu_1 + \mu_2 - \mu_1\mu_2, \upsilon_1\upsilon_2\right); \tag{5}$$

$$\varphi h_2 = \left(1 - \left(1 - \mu_2\right)^{\varphi}, \upsilon_2^{\varphi}\right); \tag{6}$$

$$h_1^{\varphi} = \left(\mu_1^{\varphi}, 1 - \left(1 - \upsilon_1\right)^{\varphi}\right)\ ; \tag{7}$$

$$E_1 \otimes E_2 = \left(\upsilon_1 + \upsilon_2 - \upsilon_1 \cdot \upsilon_2, \mu_1 \cdot \mu_2\right), \tag{8}$$

where $\alpha > 0$.

Eq. (5) and Eq. (8) are ring sum and ring product. Eq. (6) and Eq. (7) are scalar multiplication and power operator.

3.2. Expert and criteria weight calculation methods

Weights or relative importance is an important decision parameter that has significant role in determining the final ranking of alternatives. Direct assignment of such weights incurs subjectivity and bias – in order to alleviate such issues, researchers adopted two broad categories – with partial information and without partial information (Koksalmis & Kabak, 2019; Kao, 2010). In the former case, some additional overhead is involved, whereas in the latter case, no such overhead exist. Besides, many applications face difficulties in articulating some partial knowledge and in such cases, the latter category comes handy.

In this section, we discuss methods from the latter category. Weights of both experts and criteria (sometimes referred as attributes or factors) are methodically determined by considering no a priori information. Attitudinal variance and LOPCOW is presented with HyFNs for determining weights of experts and factors (criteria/attributes), respectively. As discussed earlier, the attitudinal variance takes characteristics into consideration – during experts' weight calculation. Also, LOPCOW avoids imbalances in weights of factors by considering variability and log operations.

The variance measure is a straightforward way to understand hesitation in expert preference elicitation as claimed by Kao (2010). It considers all data points for determining weights unlike other measures such as maximum and minimum that only considers extreme values for determining the weights. Furthermore, during expert weight calculation, we embed the trait of expert, which gives a realistic perspective of how human assign weights or importance to decision entities (criteria or attribute in this case). LOPCOW is an objective weighting method that is proposed by Ecer and Pamucar (2022) with the idea of determining weights by nullifying the effects of extreme values – via log function. Moreover, the method considers criteria type during normalization and determines weights by making fair distribution of importance (weights) across diverse criteria making the method not too biased on certain criterion or not too dependent of specific criterion. This method upholds the multi-criteria perspective and enables rational decision-making by assigning weights in a uniform fashion by following log function and percentage of value function.

Steps are detailed below for determining the weights of experts and factors.

3.2.1. Expert weights

Step 1: Consider decision matrices from each expert. Alternative GBMs are rated based on factors. r decision matrices are formed with $m \times n$ order.

Step 2: Transform the matrix into vector of $1 \times N$ order where $N = m \times n$. r such vectors are obtained. Determine the score by using Eq. (3). It is clear that N is obtained by multiplying the number of rows (alternatives) and number of columns (criteria/factors). If there are r experts, then we get that many number of vectors.

Step 3: Apply the variance formula (shown in Eqs. (9)–(10)) over the data from Step 2.

$$vp_l = \frac{\frac{\sum_{k=1}^{N}\left(S\left(E_{1k}\right) - \overline{S\left(E_1\right)}\right)^2}{N-1}}{\sum_l \left(\frac{\sum_{k=1}^{N}\left(S\left(E_{1k}\right) - \overline{S\left(E_1\right)}\right)^2}{N-1}\right)}; \tag{9}$$

$$vo_l = 1 - vp_l, \tag{10}$$

where vo_l is the variance value of expert l in the sense of optimistic trait and vp_l is the variance value of expert l in the sense of pessimistic trait.

Step 4: Combine the attitudinal traits by considering Eq. (11). The values from the equation are weights of experts – with consideration to both the traits.

$$vt_l = \frac{0.50 \times vo_l + 0.50 \times vp_l}{\sum_l \left(0.50 \times vo_l + 0.50 \times vp_l\right)}, \tag{11}$$

where vt_l is the total weight of expert l.

3.2.2. Factor weights

Step 5: Consider factor weight matrix of order $r \times n$. Convert the HyFNs into scores by using Eq. (3).

Step 6: Normalize the matrix by using Eq. (12). Dimension remains unchanged.

$$nor\_F_{lj} = \begin{cases} \dfrac{S\left(E_{lj}\right) - \min\left(S\left(E_{lj}\right)\right)}{\max\left(S\left(E_{lj}\right)\right) - \min\left(S\left(E_{lj}\right)\right)} & \text{when } j \text{ is Benefit} \\ \dfrac{\max\left(S\left(E_{lj}\right)\right) - S\left(E_{lj}\right)}{\max\left(S\left(E_{lj}\right)\right) - \min\left(S\left(E_{lj}\right)\right)} & \text{when } j \text{ is Cost} \end{cases}, \tag{12}$$

where: $\min(.)$ is minimum operator; $\max(.)$ is maximum operator; nor_F_{lj} is a matrix with normalized scores and each value is denoted by f_{lj}.

Step 7: Determine the weighted normalized score by considering weights of experts' and normalized scores from Eqs. (11)–(12). By applying Eq. (6), the weighted normalized score matrix is obtained.

Step 8: Calculate percentage value by using Eq. (13), which yields a vector of percentage values, which is further normalized for determining weights of factors.

$$w_j = \frac{\ln\left(\frac{\sqrt{\frac{vt_l \cdot \sum_j \left(f_{lj}\right)^2}{n}}}{\sigma_j}\right) \cdot 100}{\sum_j \left(\ln\left(\frac{\sqrt{\frac{vt_l \cdot \sum_j \left(f_{lj}\right)^2}{n}}}{\sigma_j}\right) \cdot 100\right)}, \tag{13}$$

where w_j is the weight of factor j.

3.3. HyFS-based WISP method for ranking GBMs

Ranking of GBMs (alternatives) is crucial for obtaining the ordering of GBMs. Experts provide her/his rating on each GBM as well as share their overall personal choice on each GBM. By this way, opinion of experts on the GBM's performance on each factor is obtained as well as the holistic choice on a GBM is obtained, which is considered as a crucial information of decision-making.

In many practical cases, though an alternative performs well in the factor set, the final opinion on that alternative may or may not be good. As a result, the choice vector is important for making a rational decision. WISP is a simple yet crucial rank method that resembles closely with human cognition and determines ranks by considering factor types and deviation/ratio parameters. WISP method was proposed by Stanujkic et al. (2022) by considering ratio and deviation under the additive and multiplicative contexts. Some key features of WISP that facilitates its usage in complex decision problems are: (i) non-parametric fusion of additive and multiplicative results of alternatives, which is lacking in methods such as WASPAS or COPRAS; (ii) likewise, the method is robust to scale distortion (Zavadskas et al., 2022a); and (iii) WISP is compensatory in nature, but allows controlled nonlinearity – penalizes very poor performance. These merits adds value to WISP and facilitates usage in complex decision problems.

Detailed step-by-step procedure for the algorithm is presented below:

Step 1: Consider r decision matrices with order $m \times n$ for determining the ranks of GBMs. Factors' (criteria) weights and experts' weights are obtained from Section 3.2.

Step 2: Apply Eq. (14) for determining the aggregated matrix by considering data from Step 1.

$$EA_{ij} = \begin{cases} \max_k \left(rating\right) \text{ if rating is not unique} \\ average_k \left(rating\right) \text{ if rating is unique} \end{cases}, \tag{14}$$

where EA_{ij} is the aggregated HyFN.

Eq. (14) gives aggregated value and it is determined based on the frequency of the rating by experts. If the frequency of the all rating terms is 1, then average operator is used. If the frequency of all rating terms is not 1, then maximum operator is used and the term with maximum occurrence frequency is chosen as aggregated value. If the frequency yields a tie, then break the tie arbitrarily by taking average of the terms.

Step 3: Apply Eq. (3) for determining the score of HyFN and later, weighed HyFN are determined by multiplying the choice value with the scores. Personal choices are considered for each GBM, which yields a vector of $1 \times m$ order.

Step 4: Normalize the weighted scores by applying Eq. (15).

$$NA_{ij} = \frac{EA_{ij}}{\max_i \left(EA_{ij}\right)}, \tag{15}$$

where NA_{ij} is the normalized score value.

Step 4: Determine the decision parameters viz., sum deviation, product deviation, sum ratio, and product ratio by applying Eqs. (16)–(19).

$$ds_i = \sum_{j=1}^{z} w_j \cdot NA_{ij} - \sum_{j=z+1}^{n} w_j \cdot NA_{ij}; \tag{16}$$

$$dp_i = \prod_{j=1}^{z} NA_{ij}^{\,w_j} - \prod_{j=z+1}^{n} NA_{ij}^{\,w_j}; \tag{17}$$

$$rs_i = \frac{\sum_{j=1}^{z} w_j \cdot NA_{ij}}{\sum_{j=z+1}^{n} w_j \cdot NA_{ij}}; \tag{18}$$

$$rp_i = \frac{\prod_{j=1}^{z} NA_{ij}^{\,w_j}}{\prod_{j=z+1}^{n} NA_{ij}^{\,w_j}}, \tag{19}$$

where: ds_i is the weighted sum deviation; dp_i is the weighted product deviation; rs_i is the weighted sum ratio; rp_i is the weighted product ratio.

Step 5: Determine the re-calculated deviation and ratio parameters by using Eqs. (20)–(23). Each parameter yields a vector of $1 \times m$.

$$ds_i^* = \frac{1 + ds_i}{1 + \max_i ds_i}; \tag{20}$$

$$dp_i^* = \frac{1 + dp_i}{1 + \max_i dp_i}; \tag{21}$$

$$rs_i^* = \frac{1 + rs_i}{1 + \max_i rs_i}; \tag{22}$$

$$rp_i^* = \frac{1 + rp_i}{1 + \max_i rp_i}, \tag{23}$$

where the ds_i^*, dp_i^*, rs_i^*, and rp_i^* are the re-calculated deviation and ratio values.

Step 6: Determine the final rank value and ordering of GBM by suing Eq. (24).

$$R_i = 0.25 \times \left(ds_i^* + dp_i^* + rs_i^* + rp_i^*\right), \tag{24}$$

where the R_i is the rank value of GBM i.

Higher the value of R_i, the higher is the priority. So, the GBMs are arranged in the descending order of R_i values.

Figure 1 describes the decision framework proposed and used in the study. A panel of *r* experts give their ratings of *m* GBMs over *n* factors, a vector of dimension 1×*n* of factor preferences, and a vector of dimension 1×*m* of GBM preferences. The *r* matrices of ratings of *m* GBMs over *n* factors given by the experts are used to find the expert weights. The *r* vectors of dimension 1×*n* of factor preferences is used by LOPCOW to find the factor weights. The factor weights vector of dimension 1×*n*, expert weights vector of dimension 1×*r*, and *r* decision matrices of *m*×*n* ratings of GBMs, are fed to the modified WISP method

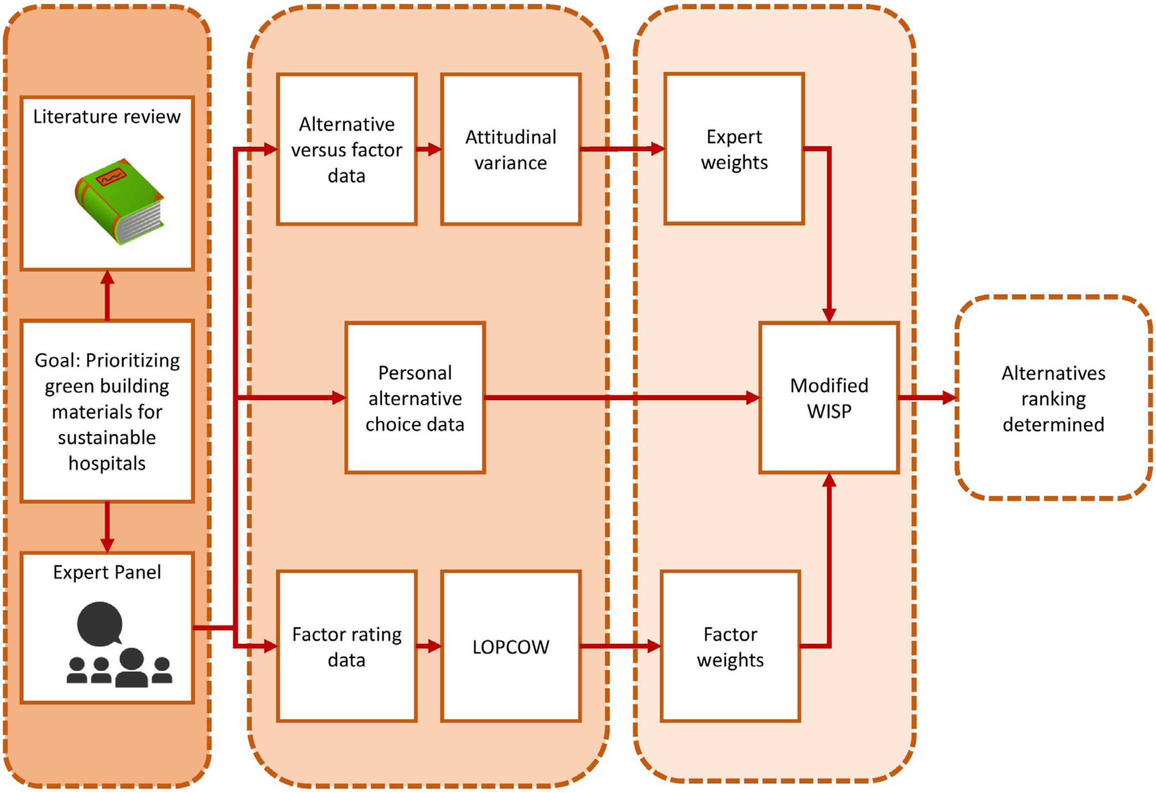

Figure 1. Workflow diagram of the proposed framework

described in Section 3.3, is used to get the rankings vector of dimension 1×m of the GBMs. The application of the proposed decision framework is given in the next section in form of a case example.

From the integrated methods presented above for determining decision parameters viz., experts' weights, criteria weights, and ranks of GBMs, certain improvements can be noted, such as:

- Experts' weights are methodically determined, which is lacking in extant GBM selection models. Besides, the presented variance method takes into consideration attitudinal trait of experts – namely, the risk appetite and risk averse traits and determines the weights of experts.
- Criteria weights are determined in extant GBM selection models, but in this framework, we calculate the weights of criteria by nullifying the effects of extreme values and also considering weights of experts, which is lacking in extant GBM selection models.
- GBMs are ranked by extant models, but consideration of personal choices on alternative GBM is missing in extant models, which is circumvented in the proposed framework.
- Finally, it must be noted that all these improvements are done along with extension of decision methods to HyFS, which is a fairly new development in orthopair fuzzy context and provides enhanced features for modelling uncertainty flexible unlike other orthopair variants, which is also a value addition to GBM selection that is lacking in extant models.

4. Example of GBM selection

In this section the proposed decision workflow has been applied on a GBM selection problem.

4.1. Background

This section presents a case example of selecting a suitable GBM for the construction of walls/floors in a health center by using the developed framework. Hospitals are actively trying to get sustainable in their lifecycle by promptly considering different aspects of the functional and non-functional services. Infrastructure construction is one such crucial aspect where hospitals must encourage adequate sustainability so as to holistically improve the three pillars of sustainability namely social, environmental, and economy.

Suppose a health center/hospital is planning to refurbish its outpatient ward and considers renovating floors/walls, the committee for infrastructure development plan to adopt green practices and support in facilitating sustainability within the construction process. In this line, GBMs are considered as a potential option and review highlighted that there are multiple options in the market and selection of suitable option is crucial to meet the trade-offs. The prioritization of GBMs would give the decision makers a flexibility to decide and support in rational decision-making. From the review of literature and practitioners advise, five materials are chosen. They are gauged based on seven factors/attributes. Four experts provide her/his rating on alternative GBMs and attributes.

The five GBMs considered are timber (cross-laminated), hempcrete, recycled steel, fly-ash concrete, and rammed earth that are denoted as m1 to m5, respectively. Factors such as carbon neutrality, thermal insulation, durability of infrastructure, material availability, indoor air quality, total cost, and complexity of architecture are considered, and they are denoted as a1 to a7. Factors a6 and a7 are cost type and the rest are benefit. We consider four decision makers who have six to eight years of experience, and they belong to academia and construction business. The decision makers provided her/his rating on GBMs and factors in the questionnaire. The anonymity of the decision makers is maintained and for this study, we denoted them as D1 to D4. The scales considered for rating are extremely low (1), very low (2), moderately low (3), low (4), neutral (5), high (6), moderately high (7), very high (8), and extremely high (9). Their respective HyFN form is (0.05, 0.99), (0.1, 0.95), (0.2, 0.9), (0.3, 0.8), (0.5, 0.5), (0.85, 0.3), (0.9, 0.2), (0.95, 0.1), and (0.99, 0.05). Table 2 illustrates the alternative GBM and criteria considered.

Table 2. Alternative GBM and criteria considered

Symbol	Material name	Source(s)
m1	Timber (cross-laminated)	Tam et al. (2017)
m2	Hempcrete	Jami et al. (2019); Wang et al. (2018)
m3	Recycled steel	Taha et al. (2017)
m4	Fly-ash concrete	Yu et al. (2017)
m5	Rammed earth	Khadka (2020)
Symbol	**Criteria/factors and type**	**Source(s)**
a1	Carbon neutrality (Benefit)	Jami et al. (2019)
a2	Thermal insulation (Benefit)	Adamczyk and Dylewski (2017)
a3	Durability of infrastructure (Benefit)	Wang et al. (2018)
a4	Material availability (Benefit)	Wang et al. (2018)
a5	Indoor air quality (Benefit)	Wang et al. (2018)
a6	Total cost (Cost)	Wang et al. (2018)
a7	Complexity of architecture (Cost)	Taha et al. (2017)

4.2. Procedure for selecting suitable GBM

The steps for calculation of the decision parameters are given below:

Step 1: Consider four matrices of 6×7 order. The rating follows 9-Likert scales.

Table 3 gives rating of decision makers on GBMs based on factors. The integer values are rating in the Likert scales and the respective HyFNs are considered for the process.

Step 2: Similarly, consider a factor weight matrix of 4×7 order. The rating follows 9-Likert scales.

Table 3. Ratings of decision makers on the five GBMs over seven factors

D1	a1	a2	a3	a4	a5	a6	a7
m1	6	5	7	6	6	4	4
m2	7	5	5	7	7	3	4
m3	5	3	7	5	4	6	5
m4	5	4	6	5	6	5	5
m5	6	7	6	5	5	4	4
D2	**a1**	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**
m1	5	6	5	6	6	3	4
m2	6	4	5	6	6	3	4
m3	5	3	7	5	4	5	6
m4	6	4	7	5	6	5	6
m5	7	7	5	6	4	4	5
D3	**a1**	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**
m1	7	4	7	6	6	4	3
m2	7	5	5	6	7	4	5
m3	5	4	6	5	4	6	4
m4	6	3	5	6	7	6	4
m5	6	6	5	6	4	3	3
D4	**a1**	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**
m1	6	5	6	7	6	3	3
m2	6	4	6	6	6	3	3
m3	6	3	5	4	5	5	5
m4	5	3	5	5	5	6	5
m5	4	5	4	4	6	3	4

Table 4. Scores for the factors from the decision makers

CW	a1	a2	a3	a4	a5	a6	a7
D1	1.45	1.45	0.75	1.62	0.22	0.75	1.62
D2	0.75	1.45	1.62	1.62	0.36	0.22	0.75
D3	1.62	0.36	0.75	0.36	0.36	0.22	0.36
D4	0.75	0.75	1.45	0.36	0.75	1.45	0.36

In Table 4, the scores of factors are provided. These values are calculated from the HyFNs that are associated with each Likert scale rating. Eq. (3) is used for determining the scores.

Step 3: Apply the procedure in Section 3.2 for determining the weights of decision makers or experts and factors/attributes. Data from Step 1 and Step 2 are considered for determining experts' weights and factors' weights, respectively. Table 5 provides the expert weights along with the intermediary values computed during the expert weight calculation steps.

Eqs. (9)–(11) are used for determining the pessimistic variance, optimistic variance, and weights of experts, which is a vector of 1×4 order. vt_l is the relative importance of an expert and the values are given by 0.246, 0.250, 0.260, and 0.244, respectively. Eq. (13) is used for determining the weights of factors/attributes and the values are calculated as 0.158, 0.130, 0.161, 0.152, 0.177, 0.114, 0.108, respectively.

Table 5. Expert weight computation

DM	VAR	vp_l	vo_l	vt_l
D1	0.254	0.2396	0.2534	0.24654
D2	0.262	0.2472	0.2509	0.24906
D3	0.298	0.2811	0.2396	0.26038
D4	0.246	0.2320	0.2560	0.24403

Note: DM is decision maker, VAR is variance.

Step 4: Consider data from Step 1 and weight vectors from Step 3 for determining the ranks of GBMs.

The Eqs. (14)–(24) are used for determining the ranks of GBMs. Recalculated decision parameters for four vectors each of order 1×5. Table 6 shows the deviation and ratio values along with recalculated values for each GBM. Personal choices on GBM are collected from each expert and they are aggregated to form a combined choice vector of 1 by 5 order. It must be noted that during the aggregation of choices, experts' weighs are considered. The aggregated choice vectors are 0.484, 0.548, 0.572, 0.567, and 0.485, respectively – obtained from simple weighted geometry operator. The vectors from experts are aggregated by using the operator to obtain the combined vector denoting personal choices of GBMs.

Table 6. Deviation and ratio values for each GBM

GBM	$d1_i$	$d11_i$	$r1_i$	$r11_i$
m1	0.6199	0.9806	15.1802	0.9265
m2	0.6519	1	16.4643	1
m3	0.2916	0.7819	3.00155	0.2291
m4	0.4087	0.8528	3.82498	0.2763
m5	0.4901	0.9021	12.1888	0.7552
	$d2_i$	$d22_i$	$r2_i$	$r22_i$
m1	–0.0392	0.9800	0.9528	0.9884
m2	–0.0196	1	0.9759	1
m3	–0.5161	0.4935	0.4838	0.7509
m4	–0.3591	0.6537	0.6405	0.8303
m5	–0.2489	0.7661	0.7010	0.8609

From Eq. (24), the rank values are determined, which yields a vector of 1×5 order. Notably, the values are 0.9688, 1, 0.5638, 0.6532, and 0.8211, respectively. The rank order of GBMs is given by m2 > m1 > m5 > m4 > m3.

5. Sensitivity and comparison analysis

In this section we perform sensitivity analysis on the results obtained in the earlier section to probe the robustness of the proposed methodology. We also examine the various pros of the proposed framework that we were observed and compare it with the existing frameworks in the literature.

5.1. Results discussion

The ranking of GBMs infer that Hempcrete (m2) > Timber (m1) > Rammed Earth (m5) > Fly-ash Concrete (m4) > Recycled Steel (m3), which infers that bio-based and low-carbon natural materials outperform industrial/recycled alternatives in overall sustainability performance. Among the seven evaluation criteria, indoor air quality (a5 = 0.177) and durability (a3 = 0.161) emerged as the two most influential factors, followed by carbon neutrality (a1 = 0.158) and material availability (a4 = 0.152). These infer that there is strong focus on health, longevity, and local resource use rather than only on cost or construction convenience.

Hempcrete (m2) ranked highest due to its superior thermal insulation, carbon sequestration potential, and contribution to indoor air quality. Its ability to absorb CO_2 during curing, combined with natural breathability, gives high priority over others in terms of criteria a1, a2, and a5. Cross-laminated timber (m1) followed closely, supported by renewable sourcing and strong structural durability, though issues of availability and architectural complexity exist, but can be managed by effective planning and strategies. Rammed earth (m5) performed moderately well because of its low embodied energy and local availability, but its lower insulation and durability offered lower priority compared to other GBMs. Fly-ash concrete (m4) ranked lower, suggesting that though it counters cement consumption, issues regarding material consistency and air quality exists. Recycled steel (m3), despite high structural reliability, is given less priority as there is high energy and cost with minimal insulation that correspond to criteria a1, a2, and a6 in the considered study.

Some policy level implications can be inferred; these findings highlight the need for integrated green-material standards that prioritize health, carbon neutrality, and resource circularity over cost, convenience during construction, and/or aesthetics. Governments and construction councils could expand subsidies and certification incentives for bio-based materials such as hempcrete and timber, recognizing their contribution to carbon decline and well-being of lives. Public procurement guidelines and green-rating frameworks (e.g., GRIHA, LEED-India) may include scores or grades for materials with verified carbon-negative or carbon-neutral lifecycles, which could promote effective adoption of GBMs in public and private construction activities.

Furthermore, localized supply-chain development could improve the availability of hemp and sustainable timber while ensuring responsible land use and inclusive distribution. Training programs for architects and engineers can reduce perceived complexity in bio-material design, thereby improving adoption. Finally, integrating green-material preferences into urban housing missions and rural infrastructure development would improve sustainable performance and support government in achieving targets under SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities), moving India's construction sector closer to the vision of carbon free or carbon zero ecosystem.

5.2. Sensitivity analysis

In this section, a sensitivity analysis of the attribute weights is conducted by systematically altering the weights assigned to each factor. The objective is to evaluate how variations in these weights impact the ranking of alternative Green Building Materials (GBMs).

The analysis is performed in two distinct scenarios:

- +10% Scenario: The original weights of each factor are increased by 0.10 individually, generating seven new weight sets (one for each attribute/factor). In each set, only one factor's weight is raised while the others remain unchanged, allowing the influence of a specific attribute's increase to be isolated and observed.
- –10% Scenario: The same process is applied in reverse, with the weights of each factor decreased by 0.10 to form another seven distinct weight sets. Again, each set adjusts only one factor at a time, enabling observation of the effect of a decrease in its importance.

In total, fourteen altered weight sets are generated: seven with weights increased and seven with weights decreased by 10%. For each set, the ranking of the available GBMs is determined anew. By comparing the results across all scenarios, as illustrated in Figure 2a and Figure 2b, the robustness of the ranking procedure can be assessed. From Figure 2a and Figure 2b, it is clear that the rank order of GBM remains intact and the alteration of weights does not have a significant impact on the ordering of GBMs. This consistency indicates the robustness of the proposed model, suggesting that the ranking procedure and decision outputs are resilient to moderate changes in the factor weights. Consequently, the selection process for sustainable healthcare construction materials is dependable, and key attributes retain their relative influence even when their assigned importance fluctuates.

5.3. Comparison – proposed vs. other GBM selection models

In this section, we compare the features of the proposed model with other state-of-the-art GBM selection models. Table 7 gives the summary of the comparison. Models such as Balali et al. (2020), Mayhoub et al. (2021), and Remadi and Frikha (2023) are compared with proposed model.

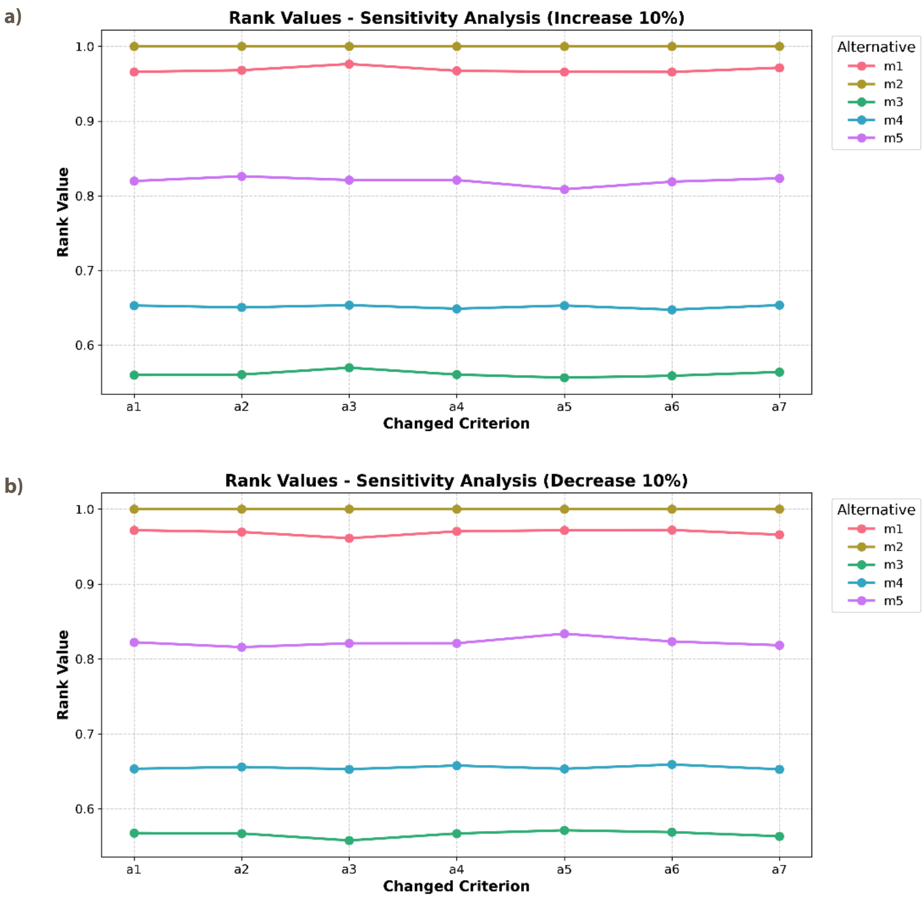

Figure 2. Sensitivity analysis by: a) increasing the criterion/factor weights by 10%; b) decreasing the criterion/factor weights by 10%

Table 7. Comparison of the proposed framework with the extant GBM selection models

Features	Proposed	Balali et al. (2020)	Mayhoub et al. (2021)	Remadi and Frikha (2023)
Modelling of uncertainty	Effective (flexible expression of preference and non-preference choices)	Low	Low	Moderate (restriction in expression of choices)
Orthopair construct	Yes	No	No	Yes
Experts' weights	Calculated	Not determined	Not determined	Not determined
Experts' attitude	Considered	Not considered	Not considered	Not considered
Consideration of expert weights in criteria weight calculation	Considered	Not considered	Not considered	Not considered
Choice-based ranking of GBMs	Yes (choice vector considered)	No	No	No

Some unique aspects of the proposed model are:

- HyFN is used to interpret rating data from experts, which allows flexible representation of both preference and non-preference grades with no strict restrictions on values.
- Experts' weights are methodically obtained by considering attitudinal characteristics of experts.
- Factors/attributes' weights are also determined methodically by considering rating from experts and their relative importance. Considering the LOPCOW method, there is scope for smooth distribution of weights among factors, which is lacking in other models. The usage of log function smoothens the spikes and facilitates even distribution of weights among factors/attributes.
- GBMs are ranked by extending WISP method to HyFN by considering weights of experts and factors. The deviation and ratio parameters are determined for calculating the grades of GBMs.

6. Conclusions

The present work adds value to the field of construction in general and healthcare infrastructure development in particular – by providing a decision system for grading/ranking GBMs that could be potentially used in floor/wall constructions. Specifically, a hybrid model is developed by considering HyFN as the medium to model uncertainty and interpret rating information from experts in an orthopair context. Key decision parameters such as weights of experts, weights of factors/attributes, and ranks of alternative GBMs are methodically calculated – thereby reducing human intervention, subjectivity/bias.

Consideration of attitudinal trait of experts is a potential aspect of the proposed model and its ability to keep a closed loop design enables better information transition and adds rationale to the decisions. Though there are merits to the framework, some limitations do exist such as: interactions among entities are not well captured, personalized contexts are not included in the framework, and missing data cannot be handled in the present form.

Some application oriented implications are: health industry is gaining lots of attention specifically in the sustainability aspect as medical waste and pollutants from the medical industry are a serious threat to the planet – in this line, this model focuses on sustainable construction of health center; incorporating GBMs into health infrastructure development is a promising step towards sustainability; and patients health recovery is also supported via such plans/propositions along with ecological benefits; consideration of sustainability aspects by contractors during such construction projects will enhance reduction of carbon emissions and add the component of sustainability with health industry, which at the present situation is seeking key attention.

Some policy level implications include: consideration of sustainability aspects and use of green practices maybe encouraged by the competent authorities before sanctioning permission for such construction projects; contractors and construction personnel maybe trained in sustainable construction practices and the industry can strongly recommend stakeholders to follow green standards during construction; and special rewards in the form of recognitions, discounts, incentives, and alike maybe promoted by different stakeholders at different levels to holistically promote sustainable construction.

Some method oriented implications from the study are: the framework can be readily used by stakeholders with certain level of training with the framework; both customers and GBM producers can be the end users of the framework – as selection as well as improvement decisions can be facilitated via the proposed model; uncertainty is an implicit entity in such decision problems and HyFN aids in better handling the situation through its flexible nature and orthopair form; and decision parameters are calculated rather than direct assignment, which reduces subjectivity/bias.

In the future, plans are made to address the limitations that emanate from this study. Also, we plan to consider other GBM materials for evaluation. Further, the prepared model can be utilized for other decision problems in construction and other areas such as contract dispute resolution, service/resource provider assessment, waste treatment method evaluation, prioritizing issues and enablers of digital transformation, and alike. Further, plans are made to consider social media platforms for detailed descriptive data that can be used along with text mining and sentiment analysis concepts for performing large-scale decision-making.

Author contributions

Raghunathan Krishankumar: Conceptualization, Data curation, Method, Software, Writing – original draft. Abhishek Yadav: Conceptualization, Data curation, Method, Software, Writing – original draft. Kattur Soundarapandian Ravichandran: Conceptualization, Method, Investigation, Review, Writing – original draft. Jūratė Šliogerienė: Method, Investigation, Review, Supervision, Writing – original draft. Edmundas Kazimieras Zavadskas: Method, Investigation, Review, Supervision, Writing – original draft.

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