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Engaging stakeholders in construction transport policy: A mass-participation framework

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ABSTRACT

In the complex landscape of social decision making, multi-criteria decision making (MCDM) provides decision makers with a structured approach to evaluate multiple alternatives based on multiple conflicting criteria. Numerous multi-criteria group decision making (MCGDM) frameworks have been developed to engage stakeholders like citizens on a large scale and to capture their diverse preferences. Real-World Application in Construction Logistics: The framework's utility and effectiveness are empirically validated through its application in a construction logistics project. This application involved gathering preferences from residents near the construction site and using these inputs to guide policy decisions, demonstrating the framework's practical impact on urban planning and development. However, current frameworks exhibit certain limitations. In recognition of this, we present the mass-participation framework for MCGDM. This innovative framework combines data collection of criterion weights via survey with representative workshops for a more holistic evaluation of alternatives. Key features of our approach include the tailored adaptation of the Revised Simos Method for surveys, which ensures intuitive weight elicitation. In addition, we introduce a clustering algorithm rooted in priority-based K-medoids techniques and employ a comprehensive set of metrics for optimal cluster number determination. The methodology is then empirically illustrated in the context of a real-world construction logistics project. The research highlights the importance of extensive stakeholder engagement for robust and inclusive construction transport and urban planning policies. Our mass-participation framework moves beyond traditional consultation by actively involving stakeholders in decision-making, allowing them to contribute both preferences and solutions. Empirical validation in the Brussels-Capital Region involved over 150 residents, whose preferences were clustered into distinct groups based on their concerns, such as noise pollution, air quality, and traffic accessibility. The majority of stakeholders favored sustainable logistics solutions, particularly electric concrete trucks, due to their potential to reduce environmental impacts. These findings demonstrate the framework's ability to capture diverse perspectives and inform sustainable policy development.

1. Introduction

In social decision-making, identifying a solution can be a complex task. Decision-makers (DMs) often navigate a multidimensional space of conflicting criteria, such as economic viability and environmental sustainability (Uzun et al., 2021). Multi-Criteria Decision-Making (MCDM) serves as a method to assist DMs in assessing several alternatives by evaluating a set of criteria (Mardani et al., 2015). However, relying solely on the judgment of a single DM may not adequately capture the complexities inherent in a given problem. For a more comprehensive understanding, Group Decision-Making (GDM) offers a broader approach by aggregating the evaluations of multiple DMs, thus providing a more nuanced ranking of alternatives (Pedrycz et al., 2011).

Traditional GDM methods typically rely on a small number of experts (Lu and Ruan, 2007). While expert insights are valuable, they often fail to reflect the diverse perspectives of the broader range of stakeholders who are impacted by the decisions being made (Freeman, 2010). This limitation is particularly significant in sectors such as social management (Munda, 2004), environmental stewardship (Salminen et al., 1998), mobility (Huang et al., 2021a, 2024c) and transportation planning (Macharis et al., 2012), where decisions influence a wide

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array of stakeholders, including non-experts like citizens. In the construction transport sector, which involves numerous and diverse actors, this issue becomes even more pronounced. While all stakeholders share a common goal – successful project completion – each actor has different motivations and concerns, as construction logistics processes are site-, actor-, and condition-specific (Brusselaers et al., 2021). The decisions made in this sector often disproportionately affect citizens, who, despite being significantly impacted by construction processes, are frequently underrepresented in decision-making frameworks (Kweit and Kweit, 1980).

A critical gap in current MCGDM frameworks is their inability to effectively incorporate the diverse views of citizen stakeholders, particularly in large-scale projects where logistical constraints, such as convening workshops or gathering reliable input from varied groups, complicate participation (Huang et al., 2021). While online surveys can be used to engage large groups, they pose challenges: citizens may have varying levels of understanding of MCDM methods, which can affect the consistency and reliability of their evaluations. Furthermore, the success of decision outcomes often depends on citizen support (Schmitter et al., 2002). If decisions do not reflect public sentiment, opposition can emerge through social movements, potentially delaying or disrupting project implementation (Glasberg and Shannon, 2010).

In light of these challenges, this research aims to address not only the methodological shortcomings of existing MCGDM frameworks but also the practical issues of engaging large-scale.[1], diverse stakeholder groups, especially citizens. Current frameworks fall short in two key areas: (1) they typically focus on expert involvement, failing to capture the broader perspectives of non-experts, and (2) they lack mechanisms to ensure the reliability of evaluations from diverse participants, especially in large-scale settings.

To address these issues, this study proposes an innovative MCGDM framework – termed the Mass-Participation Framework – designed to accommodate opinions from large-scale participant pools while ensuring the reliability of their input. The framework was field-tested in a real-world construction logistics case study, illustrating its applicability and effectiveness in capturing diverse stakeholder perspectives, including those of citizens, in a structured decision-making process.

The framework features three key highlights:

1. Adaptation of a widely employed MCDM weight elicitation technique, the Revised Simos Method (Figueira and Roy, 2002), to a survey-based setting. This facilitates the elicitation process while still yielding robust results.
2. Introduction of a priority-based clustering algorithm grounded in K-medoids methods (Kaur et al., 2014). The focus of this clustering is on the participants' ranking of criteria, which serves as the objective for the clustering process.
3. Demonstrable applicability in real-world scenarios: The framework was empirically tested on an actual construction logistics project. Surveys were administered to the residents in the vicinity of the construction site, their priorities were determined, and representatives were identified and invited to a workshop.

This framework is aimed at engaging diverse stakeholders – including citizens, local authorities, environmental groups, and construction firms – who influence or are influenced by decisions related to construction transport logistics. The framework is particularly relevant for policymakers, urban planners, and project managers who must balance competing priorities in urban construction settings. It was empirically tested in a real-world construction logistics case study in the Brussels-Capital Region, Belgium, where construction transport projects involve a multitude of stakeholders and significant environmental and social impacts. The framework integrates online surveys for initial data collection, clustering methods to group participants based on their criteria rankings, and workshops where representatives from each cluster participate in decision-making.

The paper is organized as follows: It begins with a review of existing literature concerning MCGDM frameworks designed for large-scale involvement. This is followed by a detailed presentation of the proposed framework. A construction logistic case study is then presented to demonstrate the framework's feasibility and utility in a real-world setting.

2. Literature review

2.1. Stakeholders in urban construction transport

In light of the urbanization trend (Nations, 2018), local and regional governments have concentrated their efforts on improving the built environment, which encourages the continuous construction of new buildings and the renovation of older ones (Nations, 2019). In the long run, these natural urban developments bring along more attractive, more sustainable, and more economically viable cities (Janné, 2020). Logistical operations are an essential component of the construction landscape because of the large, immobile buildings and the temporary nature of the site (Ekeskär and Rudberg, 2016). Construction transportation leads to large transport tonnages in a city (Dablanc, 2009; de Bes et al., 2018). Specifically for the city of Brussels, over 26% of heavy-duty goods vehicles (HGV) are related to construction (Brusselaers et al., 2023)

Numerous parties, such as municipalities, logistics providers and (sub)contractors, are inherently affected by the construction logistics and city development sectors (Bakhshi et al., 2016; Lehtinen et al., 2019). Therefore, it is critical to create and implement appropriate construction logistics scenarios to satisfy the needs and viewpoints of diverse stakeholders. Early stakeholder consultation and consideration of their diverse needs and perspectives are crucial to the development of goods transport strategies and policy implementations that have a higher acceptance rate among stakeholders and fewer chances of project failure (Browne et al., 2004, 2007; Lindholm and Browne, 2013; Quak et al., 2016). However, private and public players in urban freight transport often fall short in uniting their perspectives and the coordination of their activities (Fossheim and Andersen, 2017).

Given the construction logistic sector is represented by a wide range of diverse stakeholders, its stakeholders can be approached from a systems and city viewpoint, thereby taking an urban planning perspective to increase expertise on how to make construction logistic demands and how to include and oversee stakeholders in these procedures (Langley et al., 2013; Brusselaers et al., 2021). Brusselaers et al. (2021) therefore proposed a construction logistics stakeholder framework for the governance of urban development. The framework was adapted from the Multi-Actor Multi-Criteria Analysis (MAMCA) (Macharis et al., 2012; Huang et al., 2024b), which aims to enhance the decision-making process in a multi-governance setting by providing a mathematical foundation for stakeholders' preferences (Macharis et al., 2012; Ward et al., 2016; Kin et al., 2017). Therefore, such stakeholder framework can be seen as a part of a broader SMART governance concept (De Chennevière et al., 2017; Janné et al., 2021). The output of the framework proposed by Brusselaers et al. (2021) supports the project and city governance, in a multi-level governance context, and consists of 4 main actor groups, (1) construction site actors such as the contractors, clients and developers, (2) construction logistic actors including transporters, logistic service providers and consultants, (3) construction federations and research institutes, and (4) local and regional (urban mobility) authorities, which act in various inter-relational spaces. It must be noted that citizens were not included in their analysis, partly because is was not feasible to have a representative number of citizens in the online workshop given the available software at the time (during

[1] In the context of this study, we define "large-scale involvement" as the participation of more than 50 non-expert evaluators in the decision-making process.

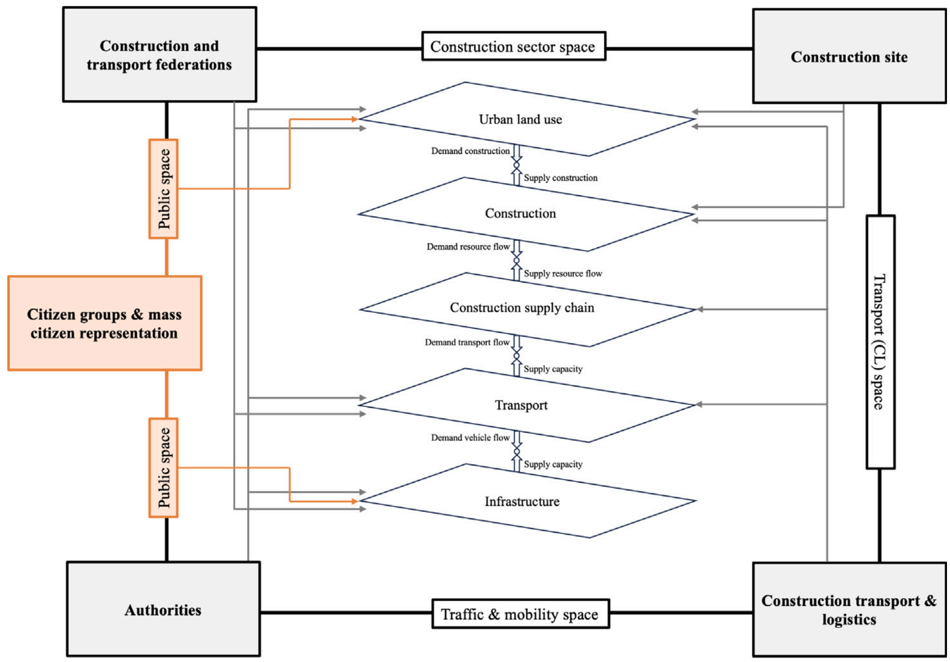

Fig. 1. Conceptual construction logistics multi-stakeholder framework and its different inter-relational spaces, with inclusion of citizens (adapted from Brusselaers et al. (2021), Fredriksson and Huge-Brodin (2022)).

the SARS-CoV-2 pandemic). Hence, further research is required with regards to citizen involvement. Similarly, Fredriksson and Huge-Brodin (2022) present a conceptual model for construction logistics systems illustrating how these numerous players interact through markets in a multi-layer design. This model was proposed to highlight which actors may impact which sorts of essential characteristics towards achieving green logistics, and therefore focuses on stakeholders who directly "own" the construction (logistics) processes, thereby making abstraction of citizens and surrounding communities (the "impacted").

Indeed, the disturbances caused during the construction works by its logistics activities are often overlooked by policy makers, and impact stakeholders outside the direct logistics system. The most important criteria in the construction logistics sector can be categorized as economic (e.g. profitable operations or transportation costs), environmental (e.g. noise, air pollution, use of public space or congestion) or societal (business climate during construction works, traffic safety impacts or accessibility) (Macharis et al., 2016; Van Lier and Macharis, 2016). Environmental nuisances from construction transportation impact the community beyond the sole perimeter of a site's fence (Ghanem et al., 2018; Fredriksson et al., 2021; Fredriksson and Huge-Brodin, 2022). These disturbances are further amplified the more simultaneous construction sites are running in a city (Brusselaers et al., 2024). The transportation-related impacts are particularly high in urban areas receptor (citizen) densities are high (Brusselaers et al., 2024), hence solidifying the need to voice the concerns of citizens in construction logistic related matters. The citizens group needs a suitable number of people in the workshop due to their diversity and heterogeneity, including residents or landowners, guests or customers, students, local businesses, employers or employees, and members of neighborhood committees.

Consequently, there is space for improvement in the context of mass participation of multi-actor multi-criteria studies. The inclusion of citizen as an actor group (in orange) is presented in Fig. 1, showing a conceptual stakeholder framework based on the ones proposed by Brusselaers et al. (2021), Fredriksson and Huge-Brodin (2022). The figure ties together the various considered actor groups, and the multi-layered construction supply chain. In this paper, the authors argue that citizen groups sit in the public space between authorities and construction and transport federations, a space in between which decisions with regards to urban land use and infrastructure in the construction supply chain are taken. The focus of this paper is highlighted in orange, and includes the citizens as a heterogeneous actor group, which acts through public spaces to influence the ends of the construction supply chain levels, i.e. urban land use and infrastructure.

2.2. MCGDM frameworks for large-scale involvement

At the outset of this literature review, we would like to extend the discussion to the importance of large-scale involvement in social decision-making problems: it seeks to democratize the decision-making process by actively incorporating public input (Stivers, 1990). Scholars such as Callahan (2002), Fischer (2000), Fukuyama (1996), King et al. (1998) contend that enhanced levels of participation foster a transparent, trust-based, and accountable decision-making environment. Greater inclusivity offers a richer data pool for decision-making (Maranville, 1984). Cooper and Wood (1974) further suggest that comprehensive participation – both in terms of participant numbers and the extent of their involvement in the decision-making stages – heightens satisfaction and influence.

Nonetheless, large-scale involvement comes with its set of challenges. Increasing participant numbers exponentially amplify the volume of information to be processed, thus elevating the risks of erroneous decisions due to data mishandling (Cooper and Wood, 1974; Pruitt, 1971). Resource implications, particularly concerning time, become considerably significant (Fitzgerald et al., 2016; Echeverria, 2000). The logistical intricacies of managing a diverse and large pool of participants exacerbate the complexity of the decision-making structure, hindering effective "face-to-face" interactions (Stivers, 1990). The expertise gap presents another challenge; participants may lack the specialized knowledge to adequately assess the decision-making alternatives (Berman, 2016; Fischer, 1993). Furthermore, the inherent diversity in participant perspectives, while enriching the discourse, could escalate into intra-group conflicts, complicating the path towards consensus (Kriplean et al., 2007).

To leverage the advantages and mitigate the challenges of large-scale involvement, numerous frameworks and strategies have been advanced. Within the scope of this paper, we selectively examine

Table 1
Comparative overview of large-scale involvement in MCGDM problems.

Authors	Content	Nr. P[a]	MCDM[b]	Clustering method	Online appraisal
Verlinde and Macharis (2016)	Assess stakeholder support for shifting to off-hour deliveries in urban Brussels.	507	AHP	Yes	No
Le Pira et al. (2016)	Evaluate priority settings for cycling mobility.	82	AHP	No	No
Ghorbanzadeh et al. (2018)	Evaluate divergent stakeholder preferences for sustainable urban transport in Mersin, Turkey.	97	IAHP	Yes	No
Ignaccolo et al. (2019)	Assess public transport preferences.	674	AHP	Yes	Yes
Bostancı and Erdem (2020)	Investigate public travel demand in Amman, Jordan.	100	FAHP	No	Yes
Keseru et al. (2021)	Assess varying stakeholder preferences concerning the future of transportation in Europe.	214	AHP and PROME-THEE	Yes	Yes
Khayatmoghadam (2022)	Ranking the factors crucial in forming organizational networks, thereby enhancing service delivery to the citizenry.	143	GAHP	No	No
Alkharabsheh et al. (2022)	Evaluate public acceptance of waste recycling apps.	200	BWM and MULTI-MOORA	No	Yes
Borna and Beheshtinia (2022)	Investigate citizens' expectations regarding municipal services.	500	AHP	No	No
Loukogeorgaki et al. (2022)	Identify and prioritize the most suitable sites for Offshore Wind Farms (OWFs) in Greece.	122	AHP	Yes	Yes
Ma et al. (2023)	Assess citizen satisfaction with municipal services.	620	FDEMA-TEL and FTOPSIS	Yes	Yes
Li et al. (2023)	Enhance Citizens' Sense of Gain in Smart Cities.	94	AHP	No	Yes

[a] Nr. P refers to the number of participants via questionnaire in these studies. In most cases, the participants are local residents (e.g. citizens in Brussels).
[b] MCDM refer to the Multi-Criteria Decision-Making methods used in the study.

frameworks that specifically address the MCGDM context. Irrespective of the diverse MCDM methods and analysis techniques employed in the aforementioned MCGDM frameworks, we conclude a non-exhaustive list into as follows (see Table 1).

The table provides a comparison of various MCGDM problems with large-scale involvement across diverse domains in recent years. The number of participants in these studies ranges from 82 to 674, indicating varying scales of stakeholder involvement. Some studies have incorporated clustering methods, most commonly using SES either as predefined or as a factor in their analysis (Verlinde and Macharis, 2016; Ghorbanzadeh et al., 2018; Ignaccolo et al., 2019; Keseru et al., 2021). GIS (Geographic Information System) is another clustering method observed (Loukogeorgaki et al., 2022; Ma et al., 2023). Some studies have adopted online appraisal processes. Unlike approaches that focus on weight elicitation, these questionnaires involve participants in a comprehensive MCDM process that can be completed entirely online. Participants are required not only to elicit weights to various criteria, but also to appraise the alternatives based on these criteria. Among the MCDM methods, AHP emerges as the most commonly employed, while variations such as interval AHP (IAHP) (Entani, 2009), fuzzy AHP (FAHP) (Liu et al., 2020) and group AHP (GAHP) (Saaty, 1989) are also employed. Other methods, like PROMETHEE (Brans and De Smet, 2016), MULTIMOORA (Hafezalkotob et al., 2019), best–worst method (BWM) (Rezaei, 2015), fuzzy TOPSIS (FTOPSIS) (Nădăban et al., 2016) and fuzzy-DEcision-MAking Trial and Evaluation Laboratory (FDEMA-TEL) (Jeong and Ramírez-Gómez, 2018) are also noted.

While these frameworks aims to involve large-scale participants with a rational manner, they also exhibit certain shortcomings. For example, some studies take the mean value of citizens' preferences, potentially neglecting divergent views. Additionally, utilizing an online appraisal process presents its own set of risks in the context of social decision-making. Participants may lack the specialized knowledge needed for accurate evaluations, thereby running the risk of misrepresenting their true preferences (Almond and Verba, 2015).

We contend that for MCGDM problems with large-scale involvement, it is generally inadvisable to have participants complete the decision-making process online. While the elicitation of criteria weights can potentially be more objective and therefore better suited for online completion, the appraisal of alternative preferences typically requires guided interaction and robust data support. We propose that the appraisal of alternative preferences should ideally be conducted in a workshop setting, where experts and facilitators can guide participants through the complexities of the decision-making process. This environment allows for real-time clarification, discussion, and negotiation, thereby increasing the reliability and validity of the results.

Traditional clustering methods based on SES or GIS certainly have value, especially for GIS when dealing with subscribers spread over large geographic areas. However, their effectiveness may diminish in smaller regions. As a result, we propose another approach that clusters participants based on their prioritization of criteria, specifically their assigned criteria weights. The rationale behind using SES or GIS data for clustering is often to capture participants with differing objectives arising from varied backgrounds or geographical locations (Arceneaux and Nickerson, 2009). However, clustering based on criteria weights can provide a more direct and meaningful segmentation of participants, ensuring that the resulting groups are highly relevant to the specific issues at hand in the decision-making process. This, in turn, contributes to a more accurate and comprehensive representation of collective preferences.

3. Mass-participation MCGDM framework: the steps and mathematical formulations

In response to the abovementioned complexities and challenges associated with large-scale stakeholder involvement in MCGDM problems, this study introduces a novel framework called the Mass-Participation MCGDM (MPMCGDM) Framework. Drawing upon the concept of 'mass-participation' from the fields of sports and public events (Smolianov et al., 2014; Murphy et al., 2015), we use the term to denote scenarios involving a large number of participants in the decision-making process (Huang, 2023). This framework is designed to encompass all relevant stakeholders, thereby providing a more holistic and inclusive approach to tackling large-scale social issues. The primary objectives of the Mass-Participation MCGDM framework are outlined as follows:

1. **Inclusivity**: To involve an extensive array of relevant stakeholders, especially when the participant number considerably surpasses those typically encountered in conventional MCGDM studies.
2. **Representation**: To guarantee that the stakeholder cross-section genuinely influenced by the decision-making scenario, capturing a broad range of perspectives and vested interests.
3. **Intuitive decision-making**: In order to effectively manage a diverse set of participants from varied socioeconomic backgrounds, the application of an intuitively, easy-to-understand designed MCDM method is imperative.

The architecture of the Mass-Participation Multi-Criteria Group Decision-Making (MPMCGDM) framework is graphically delineated in Fig. 2. This framework adheres to the traditional MCGDM procedure, commencing with the problem structuring phase. Within this initial stage, the objectives governing the decision-making process are explicitly outlined. The set of alternatives to be evaluated within this framework is denoted as $\mathcal{A}$. Alternatives refer the potential options or solutions within the decision-making framework. Criteria used to evaluate the alternative are then defined as $C = \{c_1, c_2, \dots, c_m\}$. Next, the performance indicators for these criteria should be systematically developed to ensure accurate and meaningful analysis in subsequent stages.

Following the problem-structuring phase, the second step involves a mass-participation survey. The survey is designed to capture the priorities of participants and serve as a platform for eliciting criterion weights. We recognize the logistical challenges of mass-participation, making comprehensive and time-consuming surveys impractical. To address this issue effectively, we propose to apply a survey-based revised Simos approach which aims to assist participants in expressing criteria weights intuitively.

3.1. A survey-based revised Simos method

Weight elicitation plays a crucial role in decision-making as it helps quantify the relative importance of criteria, ensuring that the preferences of DMs are accurately reflected in the evaluation process. In large-scale surveys, adapting weight elicitation methods like the Simos method can help simplify the process, making it accessible to participants with varying levels of expertise while preserving the reliability of the results. The original Simos method, rooted in a card-play game, facilitates weight elicitation for decision criteria (Simos, 1990). DMs are given a set of cards, each representing a criterion, along with a set of white cards. The cards are arranged in an order that reflects the relative importance of the criteria. White cards may be interspersed to indicate a larger perceived gap between adjacent criteria. Criteria that are considered equally important are grouped together in *ex aequo* sets, either by clipping them together or arranging them side by side.

In an extension to Simos' original methodology, Figueira and Roy (2002) introduced the ability for DMs to specify a ratio factor z, which characterizes the importance of the most important criterion relative to the least important one. Let $u = \frac{z-1}{e-1}$, where e denotes the total ranks, including white cards (each white card represents one rank). Assume that a criterion $c_k \in C$ is ranked at the jth position, making it the $e-1-j$ least important criterion. The non-normalized weight v_j for this criterion is then calculated as follows:

$$v_j = 1 + u(e-j), \quad j = 1, \dots, e, \tag{1}$$

The non-normalized weight represents the original values calculated using the equation above. These values are subsequently normalized to ensure that the sum of all weights equals 1. To normalize the weights to the interval [0,1], each criterion's weight w_j is obtained by dividing its non-normalized weight by the sum of all non-normalized weights, which ensures that the sum of all criteria weights equals one, i.e. $\sum_{j=1}^{n} w_j = 1$. While the revised Simos method offers an intuitive approach for weight elicitation, implementing an interactive card-play game in a survey setting remains challenging. To this end, our study introduces a point-scale variant of the revised Simos method in purpose of a survey design.

Let us define a point scale l, where participants assign scores ranging from 1 to l to different criteria. We instruct participants that l represents the highest importance for the criteria, while 1 signifies the least importance. At least one criterion must receive the maximum score l. The purpose of this decision is to maintain consistent options for participants to select a value for the variable, z. Although the scale used is ordinal, participants are instructed that the lowest score of l' indicates their assumption that the most important criteria are l/l' times important as the least important criteria. Unassigned scores between the least and most important criteria are treated analogously to white cards in the original revised Simos method. Accordingly, the non-normalized weight v'_i for a criterion scored at i points is calculated as:

$$v'_i = 1 + u(i - l'), \ i \in [l', l], \tag{2}$$

where $u = \frac{l/l'}{l-l'}$. After normalization, this allows us to obtain the criteria weights for one participant. Suppose we have a set of participants $\mathcal{P} = \{p_1, p_2, \dots, p_n\}$. For each participant p_i, we derive a vector of criteria weights $W_i = \{w_{1i}, w_{2i}, \dots, w_{mi}\}$ using the point-scale revised Simos method as described earlier. Combining the weight vectors from all participants, we can construct a matrix of participant-specific criteria weights, $\mathcal{W}_{\mathcal{P}}$, defined as follows:

$$\begin{bmatrix} w_{11} & \cdots & w_{m1} \\ \vdots & \ddots & \vdots \\ w_{1n} & \cdots & w_{mn} \end{bmatrix}. \tag{3}$$

The weight matrix serves two key purposes: it is used for participant clustering in step 3 and for preference aggregation in step 4, both of which are explained in the following subsections.

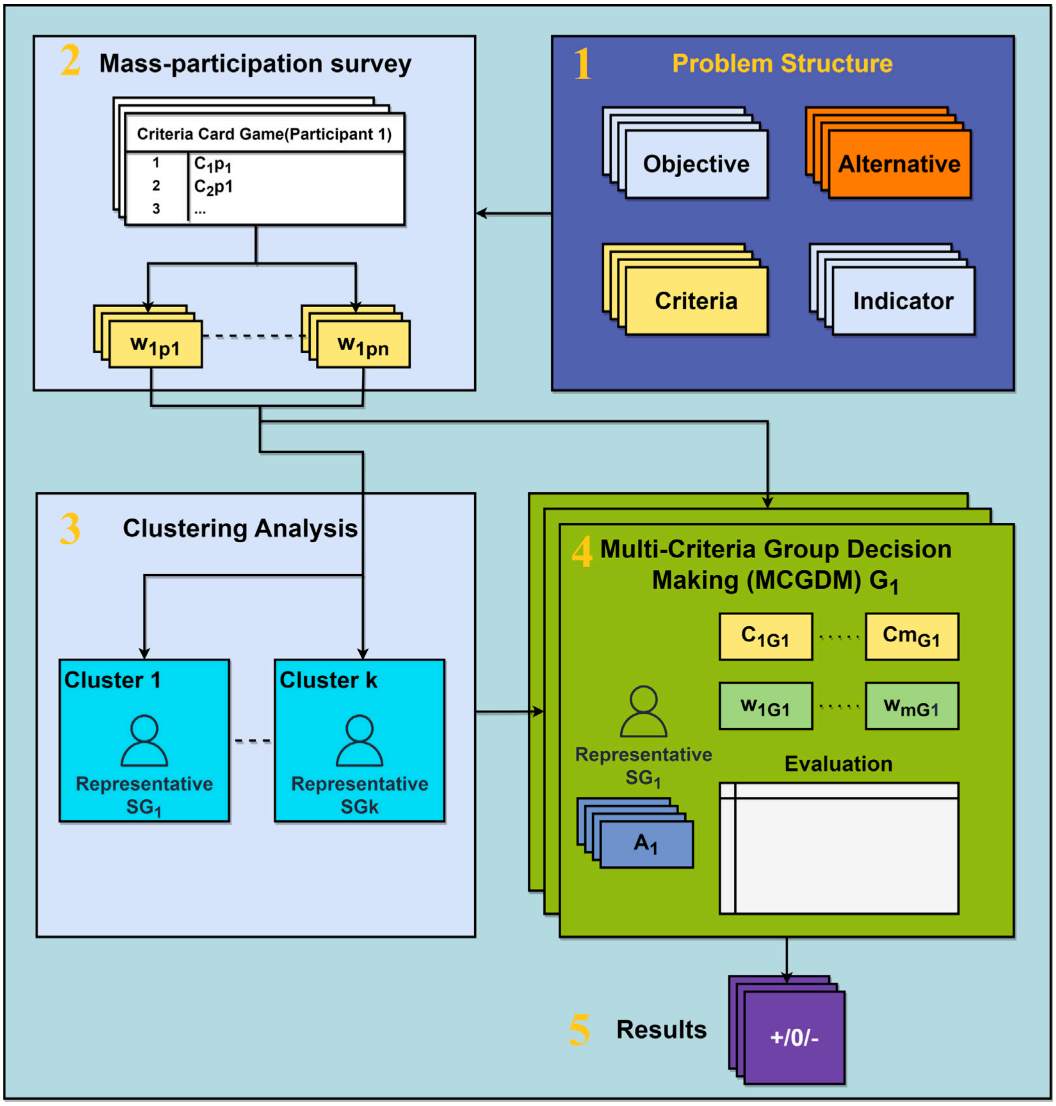

Fig. 2. Mass-Participation MCGDM Framework: The framework operates through four key phases, guiding the decision-making process from problem structuring to the final outcome.

3.2. A rank-based participant clustering method

After obtaining weights for the criteria from all participants, the subsequent stage in our framework is to cluster the participants according to their elicited priorities. This third stage involves applying techniques for clustering analysis to separate the participants into discrete groups, each with its own specific collection of decision priorities. The aim of this clustering process is not only to identify different priority sets, but also to locate representative individuals within these clusters. These representatives will then be invited to a specialized workshop, as part of step 4 in our framework. There, representatives provide a detailed assessment that acts as proxies for their respective clusters. This approach delivers a well-rounded decision-making outcome while preserving process efficiency and ease of management. Therefore, a suitable clustering technique should be utilized to fulfill the aforementioned criteria.

Among the available clustering algorithms, the K-medoids method emerges as particularly well-suited for meeting our prerequisites. This algorithm has been extensively employed in various MCGDM contexts, demonstrating a range of advantages, such as robustness to outliers and interpretability of cluster centers (Li et al., 2014; Liu et al., 2022). The K-medoids method distinguishes itself from other clustering algorithms through its selection of actual data points as cluster centers, or 'medoids.' This characteristic ensures more interpretable clustering results, as each medoid serves as a representative exemplar for its respective cluster. The algorithm starts by randomly selecting k medoids from the dataset, where k is the predetermined number of clusters. In our case, we cluster our participants $\mathcal{P}$ with K-medoids method. Let $\mathcal{P}$ be represented in a multidimensional space $\mathbf{E} = \mathbb{R}^m$, in which each dimension corresponds to the weight of C. It then iteratively refines these medoids to minimize the sum of the distances between data points and their closest medoids, resulting in a more meaningful clustering solution. The formal objective function D for the K-medoids algorithm can be expressed as:

$$D = \sum_{i=1}^{k} \sum_{p \in \mathcal{P}, p \neq x_i} d(p, x_i), x_i \in \mathcal{P}, \tag{4}$$

where $d(x, m_i)$ is the distance between a data point p and the medoid x_i of its cluster i. Note that the distance measure used in the above algorithm can be Euclidean distance, but it can also be replaced with any appropriate distance or dissimilarity measure suitable for the data type. The general K-medoids algorithm in our case can be formulated as follows:

Please note that this algorithm is just a basic approach for K-medoids, the actual implementation of the algorithm may have variations based on different heuristic methods, like the Partitioning Around

Algorithm 1 The K-medoids algorithm.

```
Input: Participants P = {p_1, p_2, ..., p_n}
    Number of clusters k
    Initialized medoids X = {x_1, x_2, ..., x_k}
    Maximum number of iterations J
Output: (Local) optimal medoids 𝒳
    (Local) optimal cluster sets S = {s_1, s_2, ..., s_k}

changed = TRUE
while changed == TRUE and j ≤ J do
    for i = 1, 2, ..., n do
        p_i ∈ S_{i_c} where i_c = arg min_{α=1,...,k} d(p_i, x_α)
    end for
    for i = 1, 2, ..., k do
        Compute the sum of pairwise distances/dissimilarities of each point in s_i to find the new medoid.
        Assign the point in s_i with the smallest sum of pairwise dissimilarities as x_i
    end for
    if current set of medoids is equal to the previous set then
        changed = FALSE
    end if
    j = j + 1
end while
```

Medoids (PAM) method (Rdusseeun and Kaufman, 1987). The core difference in the K-medoids algorithm lies in how the 'center' of each cluster is determined. In the present discussion, we suggest using a rank-based dissimilarity measure, namely the weighted Kendall's tau (Shieh, 1998), as a better alternative to the commonly preferred Euclidean or Manhattan distances in K-medoids and K-means algorithms (Park and Jun, 2009; Suwanda et al., 2020). We have several reasons for applying a rank-based approach even after acquiring criteria weights:

1. The revised Simos method, which we have adopted, inherently operates on rank-based elicitation, similarly to other surrogate weighting methodologies such as the rank sum weights (RS), rank reciprocal weights (RR) (Stillwell et al., 1981), and rank-order centroid weights (ROC) (Barron, 1992). Despite the inclusion of white cards in between criteria, this method maintains a focused concentration on the data's inherent order, giving it greater relevance in comparison to other approaches like direct rating (DR) and point allocation (PA) (Roberts and Goodwin, 2002).
2. The exclusive structure of weighted Kendall's tau comprises a weighing function that provides customization based on practitioners' needs (Vigna, 2015). Our main focus is on the priorities of the participants. This weighing function enables us to concentrate on the top-ranking criteria. Instead, using Euclidean or Manhattan approaches that calculate distances based on the dimensional space $\mathcal{E}$ may result in clustering two participants who have the same least important criteria, which is undesired.
3. Practitioners have the flexibility to tailor the weighing function to align with their distinct requirements, thereby enhancing the precision in ascertaining the significance attached to the concordance of criteria corresponding to high or low importance.

3.2.1. Rank-based distance with weighted Kendall's Tau

In the context of MCGDM, rank-based distances like Kendall's τ can be useful for comparing the relative importance of criteria as perceived by different stakeholders. Kendall's τ coefficient is commonly used to measure the correlation between ranked data, providing a robust way to assess the degree of agreement or disagreement between participants' preferences (Kendall, 1938). This is critical in MCGDM, where understanding how closely aligned different participants' rankings are can significantly impact the clustering and aggregation processes. Another method of measuring rank correlation is Spearman's rank correlation coefficient, which produces similar results but is less sensitive to small discrepancies in rank order (Pestman, 1998). However, Kendall's τ does not handle ties effectively in its original form. To address this, variants such as τ_b(Agresti, 2010) and τ_c(Berry et al., 2009) have been developed. These variants modify the calculation to account for ties in the data, making them more suitable for situations where ties are present.

Let us consider two participants, p_i and $p_{i'}$, with weight allocations for the criteria denoted as W_i and $W_{i'}$. These weights can be converted into ranking vectors R_i and $R_{i'}$, respectively. We define two real-valued vectors, $\boldsymbol{r_i}$ and $\boldsymbol{r_{i'}}$, corresponding to the rankings, where the coordinate $\langle j, j' \rangle$ $(j < j')$ is mapped using $sgn(r_{i,j} - r_{i,j'})$ and $sgn(r_{i',j} - r_{i',j'})$, allowing us to assess the rank-based correlation between participants' preferences. We define:

$$\left\langle R_i, R_i' \right\rangle : = \sum_{j<j'} \operatorname{sgn}(r_{i,j'} - r_{i,j'}) \operatorname{sgn}(r_{i',j} - r_{i',j'}), \tag{5}$$

where

$$\operatorname{sgn}(\delta) : = \begin{cases} 1, & \text{if } \delta > 0; \\ 0, & \text{if } \delta = 0; \\ -1, & \text{if } \delta < 0. \end{cases} \tag{6}$$

Eq. (5) is an inner product of dimension $\frac{m(m-1)}{2}$. By following the analogous property of the inner property, we can define:

$$\| R_i \| : = \sqrt{\langle R_i, R_i \rangle}, \tag{7}$$

Then, we have a Cauchy-Schwartz-like inequality:

$$| \langle R_i, R_{i'} \rangle | \leq \| R_i \| \cdot \| R_{i'} \|. \tag{8}$$

Kendall's τ between R_i and $R_{i'}$, i.e., the ranking similarity between p_i and $p_{i'}$, can be defined in a way formally identical to cosine similarity:

$$\tau(p_i, p_{i'}) = \frac{\langle R_i, R_{i'} \rangle}{\| R_i \| \cdot \| R_{i'} \|}. \tag{9}$$

Kendall's τ can be extended to a weighted Kendall's τ to place more emphasis on certain rank positions, making it particularly useful in decision-making scenarios where some ranking positions are more important than others. This extension incorporates a weight function that adjusts the contribution of rank discrepancies based on their relative importance. Let us define a nonnegative symmetric weight function $\eta(j, j')$, which assigns weights to the ranks of the exchanged elements. The weight function ensures that more significant rank differences are given greater influence in the overall correlation measure. Using this function, we can define the weighted Kendall's τ as:

$$\tau_\eta(p_i, p_{i'}) = \frac{\langle R_i, R_{i'} \rangle_\eta}{\| R_i \|_\eta \cdot \| R_{i'} \|_\eta}. \tag{10}$$

The properties of τ_η are proven in Vigna (2015). Then we can define the weighted ranking distance with our weighted Kendall's τ:

$$d_\omega(p_i, p_{i'}) = 1 - \tau_\eta(p_i, p_{i'}), \tag{11}$$

where d_ω ranges from 0 to 2. The lower the value of d, the closer the ranking similarity between two participants.

The utilization of K-medoids with rank-based distance in the context of our mass-participation MCGDM framework serves to efficiently partition a large set of participants into homogeneous clusters, each characterized by a distinct set of decision-making priorities. This enables us to proceed with more targeted and effective decision-making processes in subsequent steps.

3.2.2. Select the appropriate cluster number

While the clustering algorithm effectively groups participants based on different priorities, selecting an appropriate number of clusters (k) is crucial. The number of clusters directly impacts the decision-making process, as it determines how many representatives will participate in the final decision-making workshop. Choosing the right k ensures that the groups are meaningful and that the workshop remains manageable. If the number of clusters is too high, the decision-making process could become inefficient, as it would involve an impractically large number of representatives. Therefore, it is important to strike a balance between capturing the diversity of preferences and maintaining an efficient decision-making process.

Several metrics are commonly used to assess the quality of clustering, including the Davies–Bouldin index (Davies and Bouldin, 1979), Dunn index (Dunn, 1974), and silhouette coefficient (Rousseeuw, 1987). The Davies–Bouldin index measures the average similarity between each cluster and its most similar cluster, where similarity is the ratio of within-cluster (intracluster) distance to between-cluster (intercluster) distance. A lower Davies–Bouldin index indicates better clustering. The Dunn index focuses on the ratio of the smallest distance between clusters (intercluster distance) to the largest distance within clusters (intracluster distance), aiming to maximize intercluster separation while minimizing intracluster variation. The silhouette coefficient compares how well each data point fits within its own cluster versus the nearest other cluster, with higher values indicating better clustering quality.

Although these metrics have similar goals, there are key differences. The Dunn index seeks the worst-case scenario, making it useful for finding the most problematic clustering. In contrast, the Davies–Bouldin index and silhouette coefficient focus on average performance. While the Davies–Bouldin index is simpler to compute, it is limited to Euclidean distance, which may not be suitable for all types of data. The silhouette coefficient, being more flexible, is often preferred for its ability to handle non-Euclidean distances and its comprehensive assessment of clustering quality. Given the need for a manageable workshop, the silhouette coefficient is particularly useful in balancing clustering quality with practical constraints on the number of representatives.

To determine the silhouette score for a stakeholder p_i within cluster s_j, we begin by computing u_i, the mean ranking distance between that stakeholder and all other stakeholders in s_j.

$$u_i = \frac{1}{|s_j| - 1} \sum_{i' \in s_j, i' \neq i} d\left(p_i, p_{i'}\right), \tag{12}$$

where d is the ranking distance that can be found in Eq. (9). Then, the average ranking distance between member p_i and the nearest different cluster is calculated:

$$v_i = \min_{j' \neq j} \frac{1}{|C_{j'}|} \sum_{i' \in C_{j'}} d\left(p_i, p_{i'}\right). \tag{13}$$

The silhouette score of member p_i can be defined as:

$$\zeta_i = \frac{v_i - u_i}{\max\left(u_i, v_i\right)}. \tag{14}$$

In the case of the exploding increase in clusters, when there is only one member p_i in cluster s_j, we have $\zeta_i = 0$. Eq. (14) can also be written as:

$$\zeta_i = \begin{cases} 1 - \frac{u_i}{v_i}, & \text{if } v_{ii} < u_i; \\ 0, & \text{if } v_i = u_i; \\ \frac{v_i}{u_i} - 1, & \text{if } v_i > u_i, \end{cases} \tag{15}$$

where coefficient ζ is restricted to the interval $[-1, 1]$. A smaller value of u indicates a strong similarity between the member and its designated cluster, while a larger v indicates a significant dissimilarity between p_i and other clusters. To optimize ζ, it is crucial that $u_i \ll v_i$. If ζ_i approaches 1, it means that the member p_i is effectively clustered within its current cluster. In contrast, a ζ_{id} value close to -1 indicates that the member p_i would be more optimally clustered in the nearest alternative cluster. To evaluate the overall clustering performance for all members, represented by the total number n, the global silhouette coefficient is calculated as follows

$$z = \frac{1}{n} \sum_{i=1}^{n} \zeta_i. \tag{16}$$

While the silhouette score is a valuable metric for assessing overall clustering quality, relying solely on it may not be sufficient to determine the most appropriate number of clusters (k) in our context. This is particularly important because our focus is on the top-ranked criteria, which are the most influential in decision-making, rather than lower-ranked criteria such as the nth or $(n-1)$th. In the revised Simos method used for weight elicitation, these lower-ranked criteria often have minimal significance, frequently contributing just 1% or less to the overall weight. As a result, using only the silhouette score could overlook the importance of preserving homogeneity in the top-ranked criteria within clusters.

To address this, we propose a specialized metric called the same-priority rate, which captures the homogeneity of the highest-priority criteria within each cluster. This indicator helps ensure that the most critical criteria are consistently represented within clusters, complementing the silhouette score by focusing on the criteria that have the greatest impact on the decision-making process. This allows us to choose an optimal k that not only maintains high clustering quality but also ensures that the most important criteria are adequately reflected in the clustering outcomes. The same-priority rate is denoted as:

$$\rho = \frac{\sum_{i=1}^{k} \frac{\max_{\alpha} \mu_{i,\alpha}}{|s_i|}}{k}, \tag{17}$$

where $\mu_{i,\alpha}$ is the number of members in cluster i who think criterion α is the most important one. It can also be extended as the number of members who think criteria $\{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ are the top ranking criteria. $\max_{\alpha} \mu_{i,\alpha}$ finds the criterion in each cluster that most members think are the most important ones. $|s_i|$ is the number of members in cluster s_i. The same-priority rate ρ calculates the percentage of members holding the same priorities in the subgroup. When $\rho = 1$, the members are perfectly clustered, as each subgroup holds a consistent priority. A low ρ means that some subgroups have conflicting priorities. However, it is important to note that as the number of clusters k increases, the same priority rate ρ asymptotically approaches 1. This tendency is because as clusters become smaller and more specialized, there is a higher probability of internal homogeneity in member priorities, thereby inflating ρ. It should be emphasized that the primary goal of the ρ metric is not to find the value of k that maximizes ρ. Instead, this metric serves a role similar to the elbow method commonly used in clustering algorithms (Cui, 2020). Specifically, the goal is to identify the value of k at which the rate of increase in ρ begins to plateau or "elbow", signaling that additional clusters contribute diminishing returns in terms of consensus on priority among cluster members.

Finally, to ensure fair representation of different priority groups, it is important that each representative ideally speaks for a comparable number of participants. This means that for a choice of k, the number of clusters, we should optimize so that the sizes of these clusters are approximately equal. To quantify the equality of cluster sizes, we use the Gini coefficient, denoted as ϕ, which serves as a metric of inequality (Dorfman, 1979). The Gini coefficient is computed as follows:

$$\phi = \frac{\sum_{i=1}^{k} \sum_{j=1}^{k} \left| |s_i| - |s_j| \right|}{2n \sum_{i=1}^{k} |s_i|}, \tag{18}$$

where $|s_i|$ and $|s_j|$ represent the sizes of clusters i and j, respectively, and n is the total number of clusters. The numerator sums the absolute differences between all pairs of cluster sizes, while the denominator normalizes this sum by the total size of all clusters. A lower value of ϕ indicates a fairer distribution of cluster sizes, aiming for a perfectly equal representation for each priority group.

By properly employing these three indicators, we can determine a suitable number of clusters that not only provides high clustering quality, but also ensures that the members within each cluster maintain rather congruent priorities.

3.3. MCGDM workshop

After determining an appropriate value for k, the framework proceeds to the Multi-Criteria Group Decision-Making (MCGDM) phase, which culminates in a specialized workshop. Representatives (medoids) from each cluster are invited to participate, embodying the collective priorities of their respective groups. The MCGDM workshop plays a crucial role in the overall decision-making process by providing a platform where these representatives engage in structured deliberations, guided by experienced facilitators. The workshop allows for in-depth discussion and evaluation of the decision alternatives, ensuring that the diverse stakeholder preferences are directly integrated into the decision-making process.

The criteria weights assigned to the representatives are predetermined, representing the average weights of all members within their clusters, based on the revised Simos method used in the surveys. During the workshop, the representatives' primary task is to thoroughly assess the alternatives and associated criteria, contributing their group's collective judgment to the process. Using a suitable MCDM technique, they evaluate the alternatives, and these evaluations directly influence the final decision outcomes by synthesizing the diverse stakeholder inputs into a coherent and informed decision-making framework. The specific MCDM method used and the workshop format are context-dependent and may vary based on the specific decision-making scenario. For a detailed example, please refer to the next Section 4.

4. Use case

4.1. Real-life application - a construction logistics case study

The MPMCGDM framework was applied in a substantive case study focused on evaluating sustainable construction logistics scenarios (CLS) in the Brussels-Capital Region (BCR), Belgium, as depicted in Fig. 3. The BCR encompasses the municipality of Brussels and 19 neighboring municipalities, including Anderlecht, where the City Campus pilot site is located. This project is a public–private partnership between the city's development agency and the main contractor.

This pilot site provided an ideal testing ground for the framework due to several factors (Brusselaers et al., 2021). The BCR is a densely populated urban center, and Anderlecht, where the City Campus is located, has a high population density of 6,394.34 inhabitants/km^2. Additionally, the site is of significant economic importance and is strategically positioned near key transportation infrastructure, such as the R0 ring road, the E19 highway, and major inland waterways. The BCR's complex administrative structure and diverse network of stakeholders – including shopping centers, educational institutions, and local businesses – added further complexity to the project.

Initially, the case study planned a comprehensive in-person workshop involving 44 key stakeholders from the construction logistics sector. However, the challenges posed by the SARS-CoV-2 pandemic, which restricted large gatherings and citizen participation, required a shift in approach. The MPMCGDM framework addressed these challenges by leveraging its flexibility to adapt to large-scale, remote engagement. Through surveys and clustering, it enabled the collection and analysis of diverse citizen preferences while maintaining efficient decision-making processes. This approach allowed the case study to overcome the logistical constraints imposed by the pandemic and accommodate the unique attributes of large-scale citizen stakeholder groups, ensuring their voices were included in the evaluation of construction logistics scenarios despite the limitations on physical participation.

Table 2
Summarized characteristics of alternatives.

Alternatives	Descriptions
Baseline (a_1)	BAU: Suboptimal van use; Fragmented coordination; Diesel trucks
CLS 1 (a_2)	JIT delivery: Centralized logistics; Access management; Local procurement
CLS 2 (a_3)	Construction Consolidation Centre (CCC): Waterway delivery; Infrastructure shift; Material bundling
CLS 3 (a_4)	Preferred road network: Time/space constraints; Road space optimization
CLS 4 (a_5)	Electric concrete trucks: Sector-specific EVs; Time slots; Phased fuel truck fade-out

4.2. Implementation

In alignment with the MPMCGDM framework, the initial step involved structuring the problem. Objectives and alternatives had already been defined in previous research (Brusselaers et al., 2021). Four preferred Construction Logistics Scenarios (CLSs) were identified that encompass a range of policies, logistical approaches, and strategic actions designed to address the target issues. These were selected in addition to a baseline business-as-usual scenario. Each of the preferred CLSs has different characteristics and may include a mix of policies, all of which are detailed in Table 2. Next, a pre-defined set of criteria was established with citizen involvement, as outlined in Table 3 (Huang et al., 2023).

In step 2 of MCGDM, the mass participation survey was then carefully designed. Questionnaires were distributed in the residential area surrounding the pilot site. The criteria were rated by citizens using the previously described methods. Upon receipt of all questionnaires, a quality control assessment was conducted to ensure the validity and reliability of the data collected. In total, responses from 151 residents were successfully amassed, yielding a robust data set conducive for ensuing analysis. As a result, a 151×9 criteria weight matrix $\mathcal{P}_{151\times 9}$ was obtained, which served as a foundational element for further computational review.

Then, we applied clustering analysis using the K-medoids method, where the distance is the rank-based distance by applying weighted Kendall's τ. In this case, we want to give more weight to the criteria with high rankings than to those with low rankings. Therefore, the weight function is defined as $\eta_{j,j'} = 1/j \times 1/j'$ for an exchange between criteria with rank j and j'. A higher rank disagreement will result in a higher η, i.e. a sharper change.

In order to find an appropriate value for k that has high clustering quality and also suitable for a manageable workshop setting, we consider k values that result in fewer than 15 clusters. For each of these predetermined k values, we compute three different metrics: the silhouette coefficient (z), the Gini coefficient (ϕ), and a newly proposed metric, the same priority rate (ρ). We want to see the priority similarities of the top two ranked criteria within clusters, so the equation becomes (17):

$$\rho = \frac{\sum_{i=1}^{k} \frac{\max_{\alpha_1,\alpha_2} \mu_{i,(\alpha_1,\alpha_2)}}{|s_i|}}{k}, \tag{19}$$

Fig. 4 shows the performance of three different metrics over different cluster counts k. The same-priority rate ρ exhibits a local optimum at $k = 4$, which decreases slightly as k is increased to 5. After that, ρ escalates, reaching a value of 0.8 at $k = 9$. Silhouette score z reaches its local optimum at $k = 5$, indicating a possible decrease in clustering quality with increasing k. For Gini coefficient ϕ, a local minimum is reached again at $k = 5$.

Remember, the elbow method suggests that it is not just about getting the highest value for same-priority rate ρ. Instead, it is more about

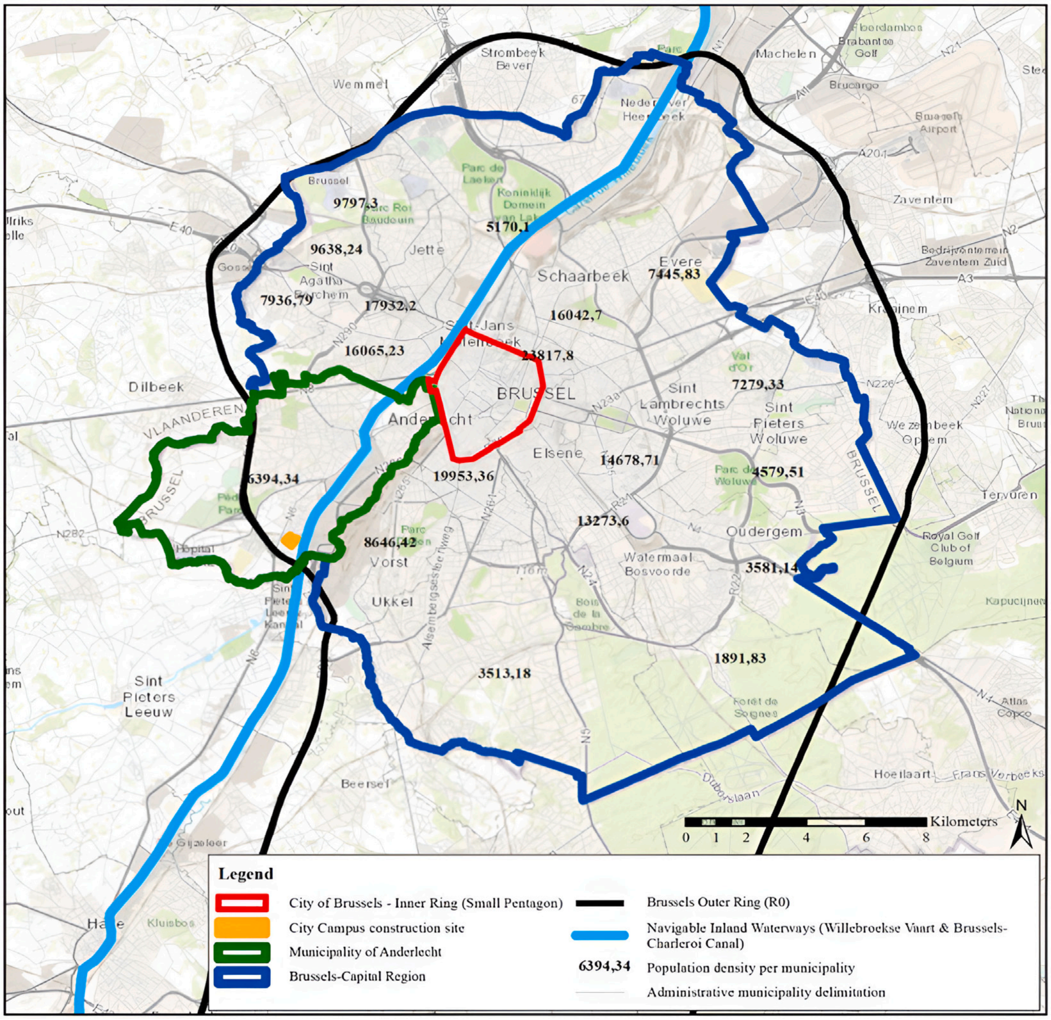

Fig. 3. The Brussels Capital Region (BCR) with its peripheral road belts, inland waterways, urban population density, and the location of the City Campus site (Brusselaers et al., 2021).

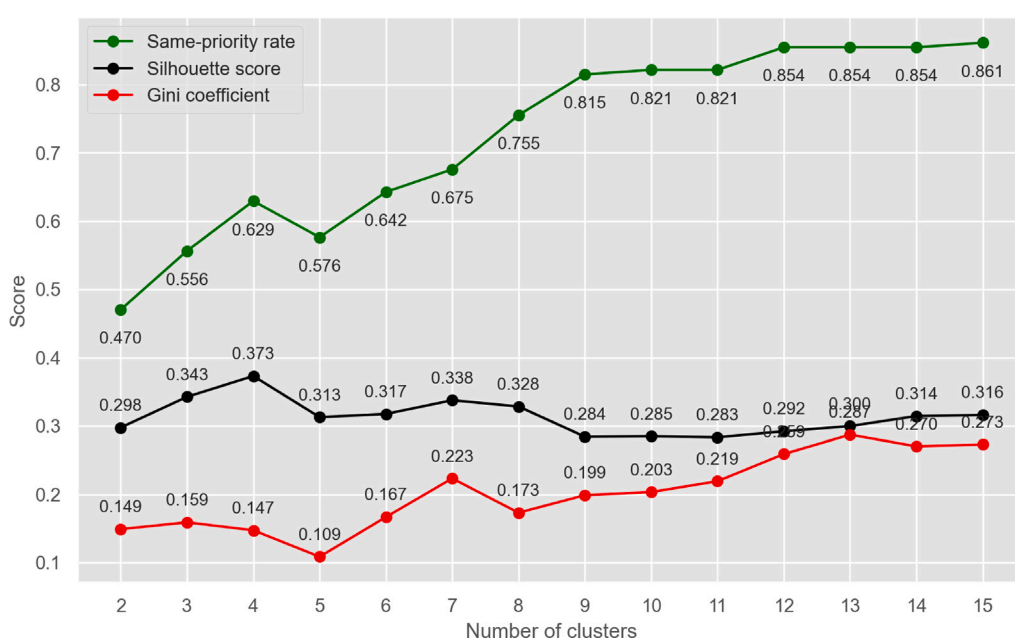

Fig. 4. Algorithm comparison on top 2 criteria.

Table 3
The criteria set for residents to evaluate.

Criterion	Name	Definition
c_1	Impact on traffic and accessibility	Impact of infrastructure works on the efficiency of a transport system; Accessibility of the region in the vicinity of the construction site by road, public transport, etc.
c_2	Noise pollution	Sound level caused by human activities, including transport, during construction projects.
c_3	Air pollution	Impact of construction works on local air quality.
c_4	Business climate during construction works	Attractiveness of the area in terms of business opportunities.
c_5	Landscape quality	Visual nuisances in the surrounding environment.
c_6	Attractiveness	Recreational facilities in and around the construction zone.
c_7	Climate change	Global impact of construction works on greenhouse gas emissions.
c_8	Social and economic revitalization	Impact after finishing the construction site.
c_9	Biodiversity	Impact of construction works on an area of nature in the vicinity.

Table 4
Summary of cluster results.

Cluster	Priorities (top two ranked criteria)	No. of members
1	c_1, c_2	40
2	c_7, c_9	29
3	c_8, c_1	28
4	c_2, c_3	54

finding an “elbow point” or local optimum. Given this, $k = 4$ emerges as a possible choice, primarily because the Silhouette score also realizes a local optimum at this number. At the same time, while $k = 5$ may offer more homogeneous cluster sizes, $k = 4$ is also a comparatively low Gini coefficient, reinforcing its viability. Consequently, $k = 4$ is selected as the optimal cluster count.

With $k = 4$, the algorithm clustered the participants into four groups. As shown in Table 4, cluster 1 is most concerned about the impact on traffic and accessibility, as well as noise pollution. Cluster 2 prioritizes issues related to climate change and biodiversity. Cluster 3 places the highest importance on social and economic revitalization and impact on the traffic and accessibility. Cluster 4 is primarily concerned about noise pollution and air pollution.

Based on the clustering result from the algorithm, the medoids of the clusters will be selected as the representatives of the subgroups. Prior to the selection, it is necessary to numerically express the heterogeneity among the medoids of different clusters. Thus, the pairwise ranking distance matrix among the 4 medoids are illustrated as (20), where the distance values are rounded up to 3 decimal places, which shows the diversity of the clustering. They will be invited to the following decision-making workshop.

$$\begin{bmatrix} 0.000 & 0.748 & 1.564 & 0.860 \\ 0.748 & 0.000 & 1.362 & 1.195 \\ 1.564 & 1.362 & 0.000 & 1.205 \\ 0.860 & 1.195 & 1.205 & 0.000 \end{bmatrix}, \tag{20}$$

4.2.1. Decision-making workshop

With the completion of the project and the subsequent dispersal of participants, traditional methods of directly engaging them became impractical. To address this challenge and simulate the diverse perspectives of citizens, we organized a decision-making workshop that used researchers as proxies for the actual citizen representatives. These researchers were selected based on their expertise and understanding of the citizens’ perspectives as outlined in the cluster analysis.

The primary objective of this workshop was to provide a simulated yet substantive evaluation of the decision scenarios, reflecting what the input of the citizens themselves might have been had direct participation been possible. Each researcher was fully briefed on the profiles of the citizen groups they represented to ensure that they could represent the interests and preferences identified during the initial data collection phase.

The designated hypothetical representatives are asked to evaluate various alternatives. During this evaluation, it is not necessary for them to re-determine the weights of the criteria. Instead, the weights assigned to the representatives are the barycenters (centroids) of the weight vectors derived from their respective cluster, i.e. subgroups. This method ensures that the representatives’ weights accurately reflect the consolidated priorities of the clustered participants, since individuals within each subgroup have similar priorities. The weights assigned to each subgroup are detailed in the table below:

The representatives employ the Analytic Hierarchy Process (AHP) for preference elicitation (Saaty, 1989), which has been successfully implemented in other stakeholder groups as documented by Brusselaers et al. (2021). The AHP method is particularly apt for this evaluation as it enables stakeholders to conduct qualitative assessments of the alternatives through pairwise comparisons. This approach facilitates a structured and systematic analysis, allowing participants to articulate and prioritize their preferences effectively. The evaluation process is conducted using the MAMCA software (Huang et al., 2020, 2024a), facilitating comparisons between the results from various stakeholder groups to draw conclusive insights for the study later. In each cluster of citizens, once the preferences for the alternatives on individual criteria are elicited using AHP, the overall preference for each alternative can be aggregated through a weighted sum approach:

$$\gamma_i(\cdot) = \sum_{i'=1}^{m} w_{ii'} \cdot \gamma_{ii'}(\cdot), \tag{21}$$

where $\gamma_{ii'}(\cdot)$ represents cluster i representative’s preference of an alternative with respect to criterion i', and $\gamma_i(\cdot)$ denotes the aggregated preference. The results of the alternative preferences for the subgroups are presented in the following section:

The table provided in Table 6 presents the aggregated preference scores for each alternative across different clusters. A close examination of these results reveals general similarities in preferences across the clusters, indicating a broadly consistent set of priorities among the different subgroups. Alternatives a_5 and a_4 are favored across all subgroups, suggesting that these alternatives best align with the

Table 5
Criteria weights of subgroups.

Cluster	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
1	0.162	0.127	0.115	0.093	0.100	0.109	0.089	0.113	0.093
2	0.108	0.114	0.118	0.085	0.120	0.091	0.140	0.093	0.130
3	0.129	0.115	0.120	0.094	0.101	0.107	0.102	0.155	0.079
4	0.107	0.149	0.141	0.095	0.100	0.104	0.100	0.109	0.094

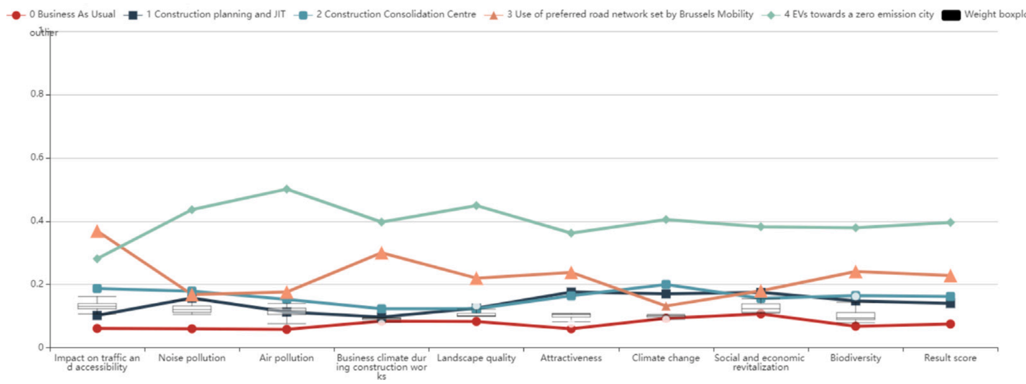

Fig. 5. Citizen overall preference. The lines in the chart depict the average preferences for different alternatives across various criteria, alongside their cumulative preferences. Accompanying each criterion, a box plot illustrates the variance in weights across subgroups, providing insights into the consensus or disparity among different stakeholders.

Table 6
Alternative preference result of subgroups.

	a_1	a_2	a_3	a_4	a_5
cluster 1	0,076	0,131	0,148	0,255	0,389
cluster 2	0,074	0,129	0,144	0,241	0,413
cluster 3	0,079	0,171	0,167	0,239	0,305
cluster 4	0,069	0,128	0,188	0,216	0,300

overarching priorities identified within the group. In contrast, a_1 is uniformly the least preferred option, highlighting a common consensus on its relative inadequacy compared to other alternatives. However, the preferences for a_2 and a_3 display notable variability among the clusters. Specifically, clusters 1, 2, and 4 exhibit a stronger preference for a_3 over a_2. This trend is reversed in cluster 3, where a_2 is preferred over a_3. Despite these divergences, the preference margins between a_2 and a_3 are relatively narrow, with a maximal observed difference of 0.04. This close margin suggests that while there is a discernible preference, the distinctions between a_2 and a_3 are not pronounced.

Based on the results, it is feasible to aggregate the clusters' results to illustrate the overall citizen preferences towards alternatives. An average preference can be calculated, reflecting the consistent preferences among different subgroups as follows:

$$\overline{\gamma}(\cdot) = \frac{1}{k}\sum_{j=1}^{k}\gamma_j(\cdot), \tag{22}$$

where $\overline{\gamma}$ denotes the average preference across all clusters and γ_j represents the preference scores for each alternative in cluster j. This formula allows us to calculate a comprehensive overview of citizen preferences, integrating the data from all clusters. The aggregated preferences are then visualized in the MAMCA software, as illustrated in Fig. 5.

Similar to Table 5, the chart reveals that certain criteria exhibit closely aligned weights, conversely, other criteria display variability, reflecting divergent perceptions or priorities among the subgroups. Notably, alternative a_5, "Electric Concrete Trucks", consistently emerges as the preferred choice across nearly all criteria, except for c_1, "Impact on Traffic and Accessibility". This suggests that while this alternative is favored for its potential to contribute to sustainability and environmental quality – emphasized by its dominant performance in criteria related to ecological and air quality improvements – it may not optimally address traffic and accessibility concerns.

5. Discussion

The mass-participation framework enables the comprehensive collection of citizens' preferences, capturing both high-level orientations and detailed insights. The depth and richness of the data gathered through this framework provide extensive insights into the priorities of the citizens, enhancing our understanding of their diverse perspectives and needs.

Using the demographic information from the survey, we can derive a rational justification for the preferences expressed by residents within the subgroups. For instance, residents with children demonstrated a strong inclination towards criteria such as "climate change" and "biodiversity", driven by their concern for the environment that their offspring will inherit. This aligns well with a_5 (electric concrete trucks), which addresses noise and air pollution, making it the preferred alternative for this group. On the other hand, younger participants, likely at an early stage in their careers, prioritized "Social and Economic Revitalization" and "Traffic and Accessibility Impacts", reflecting concerns related to employment, mobility, and urban living. This group's preferences align more closely with a_3 (preferred road network), which aims to optimize road use and enhance traffic flow during construction.

Clustering participants based on their ranking of criteria provides a more nuanced and direct method of segmenting stakeholders. This ensures that each cluster reflects a unique set of priorities, allowing their perspectives to be considered in the decision-making process. For example, participants who ranked environmental criteria highly showed a clear preference for a_5, emphasizing electric concrete trucks due to their potential to reduce construction-related noise and air pollution. Conversely, participants concerned with urban mobility and economic impacts were more supportive of a_2 (construction planning and JIT) and a_3, which focus on improving logistical efficiency while maintaining accessibility. The clustering results derived from the workshop provide valuable insights that directly inform construction logistics policies. By identifying distinct priority groups and linking their preferences to specific sustainable CLS, policymakers can tailor their approaches to address the concerns of each group.

The results from these clusters were incorporated into the overall decision-making framework using the MAMCA method, which compares stakeholder preferences across different construction logistics scenarios. As illustrated in Fig. 6, the citizen group generally aligned

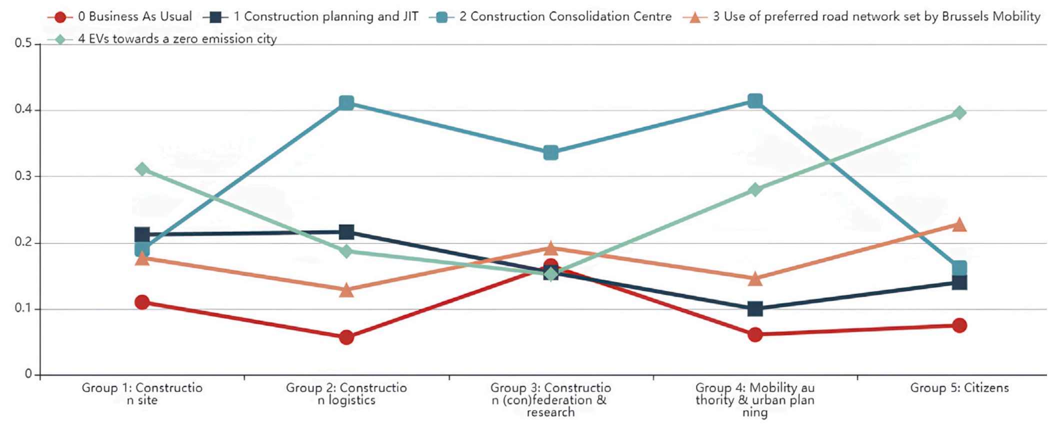

Fig. 6. MAMCA multi-actor view. The lines in the chart depict the preferences for different alternatives across various stakeholder groups.

with the authorities on a_1 (business-as-usual), a_2, and a_4 (use of preferred road networks). However, notable discrepancies emerged with regard to a_3 (construction consolidation centers). While authorities favored this solution for its logistical efficiency, citizens felt it did not sufficiently reduce local disturbances. On the other hand, a_5 (electric concrete trucks) was highly favored by citizens due to its positive impact on noise and air pollution, aligning with their environmental concerns.

By clustering participants based on their criteria rankings, the process ensures that each cluster's unique priorities are well represented in the decision-making workshop. Representatives from these clusters contribute their group's perspectives, ensuring a balanced and inclusive process. This approach contrasts with traditional consultation frameworks, where stakeholders typically have limited influence over final decisions (Davidson, 1998). By actively involving representatives, our mass participation framework creates a more democratic and inclusive decision-making model, ultimately leading to more comprehensive and sustainable policy outcomes. In summary, the mass-participation framework has proven to be a powerful tool in capturing diverse stakeholder preferences and integrating them into sustainable construction logistics policy development. Based on the workshop results, several practical recommendations for sustainable construction logistics policies can be made:

1. Adoption of Electric Vehicles: The strong citizen preference for a_5 (electric concrete trucks) highlights the need for policies that incentivize the use of low-emission vehicles in urban construction, reducing the environmental footprint of logistics operations.
2. Enhanced Traffic and Accessibility Measures: The strong support for a_3 (preferred road networks) from younger participants points to the need for infrastructure planning that prioritizes traffic flow and accessibility, particularly in densely populated urban areas.
3. Inclusive Policy Development: The mass-participation framework should be integrated into future urban planning efforts to ensure that policies are both inclusive and reflective of diverse stakeholder preferences. This approach fosters democratic engagement and leads to more equitable and sustainable outcomes.

6. Conclusion and future work

The field of social decision-making, with its inherent complexity and multiple criteria, requires methodologies that incorporate a wide range of perspectives. In the construction logistics and urban development sectors, numerous stakeholders are involved, including municipalities, logistics providers, (sub)contractors, and, most importantly, citizens. These projects directly affect local communities, making it essential to include citizens, who often experience the most significant impacts from construction-related activities, such as noise, pollution, and traffic disruptions. In order to develop transport plans and policies that are broadly accepted and reduce the risk of project failure, it is critical to involve stakeholders early in the decision-making process, ensuring that their diverse demands and viewpoints are considered.

However, harmonizing the viewpoints of corporate and public entities, particularly when integrating the opinions of large, heterogeneous citizen groups, remains a significant challenge. Citizens are often excluded from meaningful participation in construction logistics decision-making, despite being disproportionately affected by the outcomes. The MPMCGDM introduced in this study addresses this gap by offering a novel approach that enables large-scale participation without compromising the quality or relevance of the evaluations.

The framework integrates surveys and workshops to capture a broad range of stakeholder insights, including those from traditionally underrepresented groups such as citizens. These insights are then channeled through representative individuals who engage in a comprehensive MCDM process during guided workshops. The process begins with problem structuring, followed by a survey-based adaptation of the Simos method to gather information on criteria priorities from large stakeholder groups. Participants intuitively elicit criteria weights, which are subsequently used to cluster participants based on their ranking of priorities. The K-medoids clustering technique, grounded in a rank-based distance metric using the weighted Kendall's τ coefficient, ensures that the clusters reflect the most important priorities of different subgroups.

The proposed framework extends the decision-making into a comprehensive participatory process. Unlike previous frameworks that either rely solely on a survey stage – where participants are often not fully guided – or omit a discussion phase due to the impracticality of holding a workshop for a large number of participants, our framework addresses these limitations. Additionally, other models may directly select representatives for a workshop without a detailed clustering or selection process, lacking rational justification. In contrast, our approach systematically captures the priorities of stakeholder groups through surveys, allowing us to identify key representatives from these groups, ensuring that their voices are accurately represented in the decision-making process.

The empirical results demonstrate the framework's effectiveness in identifying stakeholder preferences and facilitating decision-making that balances the diverse interests of municipalities, logistics providers, contractors, and citizens. By integrating these varied perspectives early in the process, the framework ensures that construction logistics policies and solutions are more likely to be accepted by all stakeholders.

The practical implications of this research are significant. Decisions in areas such as social management, environmental sustainability, and transportation planning affect large segments of the population. This framework not only provides an academically robust methodology for stakeholder engagement but also addresses a critical social need. By embedding stakeholder priorities into the decision-making process, particularly the voices of citizens, the framework contributes to more inclusive, democratic, and sustainable policy development in urban construction logistics.

In this study, we identified several limitations and possible direction for the future work. One of the major limitations of this study is that the full framework, including all steps, was not applied in a real-world scenario. Although insights were gained from the first three steps, the workshop, which is an integral part of the process, was conducted in a simulation setting due to project constraints. The natural progression for future work would be to apply the entire framework, including the workshop component, to a real-world decision-making scenario. This would provide a comprehensive understanding of its effectiveness, challenges, and potential areas for refinement. In turn, this allows for an urban planning approach to gain a deeper understanding of how to develop construction transport policies, while involving and manage stakeholders in these processes.

While our clustering methodology based on criteria ranking has shown potential, it inherently focuses on explicit priorities without delving into the underlying structures of stakeholder interactions. While effective in many contexts, such a method may not capture the intricate dynamics or patterns of influence within a stakeholder group that can significantly shape the collective decision-making process. A promising way to overcome this limitation lies in the field of social network (Li et al., 2022). By integrating insights from this discipline, our framework can be extended to understand and incorporate relational dynamics within the participant pool. This will ensure that influential nodes or groups within the social network are adequately represented in the decision-making process, thereby capturing both overtly expressed and latent priorities. Such a multi-pronged approach to stakeholder segmentation and representative selection can further refine the accuracy and comprehensiveness of collective decision outcomes.

CRediT authorship contribution statement

He Huang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicolas Brusselaers:** Writing – review & editing, Investigation, Formal analysis, Conceptualization. **Yves De Smet:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Cathy Macharis:** Writing – review & editing, Supervision, Conceptualization.

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