# CHAPTER 2
# PRELIMINARIES AND LITERATURE REVIEW

*This chapter introduces the basic knowledge of preference representation structure, fuzzy preference relation, consensus-reaching process, and blockchain, which are fundamental to understanding the consensus-based group decision-making presented in the thesis. After that, we provide a comprehensive literature survey on the CRP for the purpose of understanding the issues and research gaps related to existing CRPs.*

## 2.1 Preliminaries

In consensus-driven group decision-making, a group of decision-makers provides their preferences that are consolidated and aggregated to obtain the collective preference, which is to be agreed upon by all the participants. The preference representation structure is an essential entity in the GDM that needs to be understood before moving on to the consensus process. The consensus process is different from the usual decision-making process as it provides feedback to the DMs until it reaches a solution that is agreed upon by all or many. Thus, the CRP consists of mainly two processes: the consensus measure and the feedback process. In this section, we describe the preference representation structure, the methods of CRP, a blockchain technology that helps to establish decentralized group decision making and other related matters regarding the design of the CRP for the identified issues.

### 2.1.1 General CRP Framework

To achieve the goal of group decision-making, in recent decades, CRP has been the major research hotspot. The framework shown in Fig. 2.1 summarizes most of the consensus-reaching models that include the four main procedures [11]: first, the DMs express their preferences in the specified preference representation structure; secondly, an aggregation function is used to aggregate the individual preferences into collective preference; next utilize the approach of consensus measure to obtain the degree of agreement among the DMs and at last to generate the preference modification advice employ the feedback mechanism. Repeat these steps until the predefined consensus threshold is achieved.

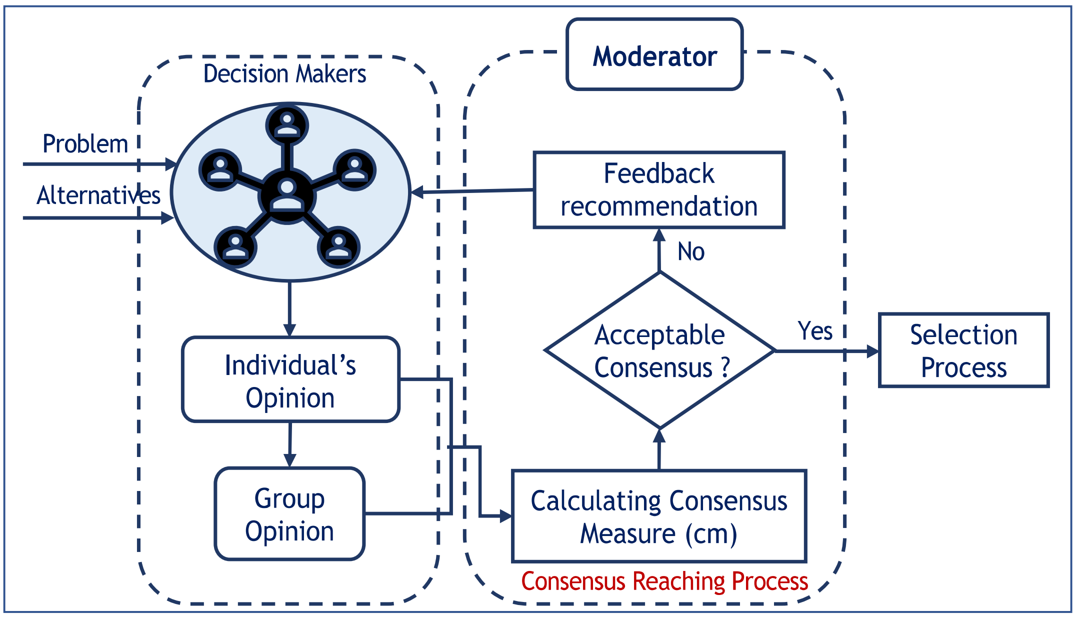


*Fig. 2.1: General CRP in Group Decision Making*

#### 2.1.1.1 Preference Representation Structure

This section is devoted to understand the way in which the information is provided by the DMs. The concept of preference representation structure in decision making is referred to as the format in which the DMs provide their opinions. DMs could give their opinions in preference orderings, utility functions, or preference relations. In general, the DMs provide their preferences basically in three types of information: numeric [12][13], linguistic [14], and heterogeneous [15]. The numeric information is given using the preference structures such as fuzzy preference relations (FPRs), multiplicative preference relations (MPRs), hesitant fuzzy preference relations (HFPRs) and so on. Apart from these, some other numeric structures are also used such as utility functions or the preference orderings. Other mode of expression of preference is by using the linguistic information, which is helpful in modelling the linguistic uncertainty. In this regard there are many types of linguistic structures such as linguistic preference relations (LPRs) or hesitant fuzzy linguistic preference relations (HFLPRs) of whose elements are represented by linguistic terms that belongs to a predefined linguistic term set. Different DMs may use different preference formats so as to represent their individual preferences over alternatives, such a representation structure is called as heterogenous preference structure is defined. Among these representation structures, the fuzzy preference relation is the most widely used representation [12][13], effective in modelling the decision situations and provides flexibility to the decision-makers in expressing the real opinions than any other representation structure. Of all the mentioned representation structures, the fuzzy preference relation is made use of throughout this thesis and is discussed below in detail.

**a). Fuzzy Preference Relations**

Let $d = \{d_1, d_2, \dots, d_m\}$ be the set of $m$ decision makers. Let $X = \{x_1, x_2, \dots x_n\}$ be the set of $n$ alternatives. Here, we introduce the widely used fuzzy preference relation in the GDM.

***Definition 2.1*** [16]*:* Additive preference relations (also called fuzzy preference relations) on a set of alternatives $X$ is a fuzzy set on the product set $X \times X$, i.e., it is characterized by a membership function $\mu_f : X \times X \to [0,1]$.

An $n \times n$ preference matrix $V^p = (v_{ij}^p)_{n\times n}$ is provided by the decision maker $d_p$, where $v_{ij}^p \in [0,1]$. $v_{ij}^p = \mu_f(x_i, x_j)\ \forall i, j \in \{1, \dots, n\}$ is the preference degree of alternative $x_i$ over $x_j$ by the decision maker $d_p$. $v_{ij}^p > 0.5$ indicates that alternative $x_i$ is preferred over $x_j$, $v_{ij}^p < 0.5$ indicates that $x_j$ is preferred over $x_i$, $v_{ij}^p = 0.5$ indicates that there is indifference between $x_i$ and $x_j$, and $v_{ij}^p = 1$ indicates that $x_i$ is absolutely preffered over $x_j$. In the fuzzy preference relation, if pairwise comparison matrix $V^p = (v_{ij}^p)_{n\times n}$ where $v_{ij}^p \in [0,1]$, follows the property of reciprocity i.e. $v_{ij}^p + v_{ji}^p = 1\ \forall\ i,j \in \{1,2,\ldots,n\}$, then the matrix $V^p = (v_{ij}^p)_{n\times n}$ is called the reciprocal preference relation [17]. In this study, we assume that the decision makers express their opinions using fuzzy preference relation following the property of reciprocity.

#### 2.1.1.2 Aggregation Function

In CRPs the aggregation function is in general used to combine the preferences of the individual DMs to obtain the collective preference. Different aggregation operators, such as the weighted average (WA) operator, the power average [18], and the ordered WA operators [19], can be used to aggregate the preferences of the DMs to obtain the collective or group preference matrix. All these aggregation operators are applicable to the proposed model, whereas based on the aggregation functions used, the decision result may vary. Let $V = \{V^1, V^2, \ldots, V^m\}$ be the preferences provided by the set of DMs. Let $w = \{w_1, w_2, \ldots, w_m\}$ be the weight vector, where $w_p \in [0,1]$ and $\sum_{p=1}^{m} w_p = 1$. Let $V^c$ be the collective preference obtained by using aggregation function with weight vector $w$. Hence, using WA aggregation function the group preference could be obtained as follows:

$$(V^c) = WA(V^1, V^2, \ldots, V^m) = \sum_{p=1}^{m} w_p \,.\, V^p \tag{2.1}$$

Assigning weights to the DMs is an important factor in GDM, and various methods are present to determine weights of the individual DMs such as the multi-criteria decision-making technique [20], social network-based methods [21], AHP based methods [22]. As this study does not focus on deciding the individual's weight, we directly assign the weights in this work.

#### 2.1.1.3 Consensus Measure

Conventionally, the consensus process is defined for the full and unanimous agreement, which is defined by the hard consensus only [11]. However, it is difficult to achieve unanimity, and also it may not be necessary to most of the cases. In contrast, the concept of "soft" consensus is proposed and now used widely which led to the concept of consensus degree with degree of measurement [23]. The aim with the soft consensus degree is to better reflect the partial agreement among the DMs and to guide CRP until predefined consensus is achieved.

The consensus measure quantifies the distance between the DMs' preference and the collective preference [6], [24]. Generally, the consensus is calculated either based on the similarity of opinion to the collective opinion or based on the similarity of opinion between pair of experts. Without loss of generality, this thesis adopts the first way to measure the consensus of the DMs.

Let $V^p = (v_{ij}^p)_{n\times n}$, where $v_{ij}^p$ denotes the preference degree of the alternative $X_i$ over $X_j$. Let $V^c = (v_{ij}^c)_{n\times n}$ be the group preference obtained using Eq. 2.1, Based on [15], the consensus level of a DM is calculated based on the degree of deviation between the individual preference matrix $V^p$ and the collective preference matrix $V^c$, given in Eq. (2.2).

$$D(V^p, V^c) = \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} d(v_{ij}^p, v_{ij}^c)}{n \times (n-1)/2} \tag{2.2}$$

Here, $d(v_{ij}^p, v_{ij}^c)$ is the distance between $v_{ij}^p$ and $v_{ij}^c$. Based on the obtained degree of deviation $D(V^p, V^c)$, the degree of consensus between the individual preference matrix and the group preference matrix denoted as $CD(V^p, V^c)$ is defined as:

$$CD(V^p, V^c) = \frac{1}{1 + D(V^p, V^c)} \tag{2.3}$$

Once the consensus degree of each DM is obtained, we can obtain the group consensus level given as $cl = \sum_{p=1}^{m} w_p \times CD(V^p, V^c)$ where $w_p$ is the weight associated with the DM $d_p$ and $\sum_{p=1}^{m} w_p = 1$. The group consensus level $cl$ can now be compared with the minimum required consensus degree, also called consensus threshold denoted as $\lambda \in [0,1]$. The closer the value of $cl$ to 1, the higher is the consensus level among the DMs. And, if $cl \geq \lambda$, then the collective preference obtained will be the final group preference value. Otherwise, the DMs with lower consensus degree, called here as inconsistent DMs, will be identified, and some improvement suggestions would be provided to those DMs by employing the feedback mechanism. Usually there does not exist any unified method to decide the consensus threshold parameter $\lambda$. Recently, Chao et al. [25] established a data envelopment analysis (DEA) benchmark method for determining a consensus threshold, but it is concluded that there is no direct impact of consensus threshold on the consensus efficiency. Therefore, most commonly the value of consensus threshold is determined based on the problem specification. Some suggestions for setting the parameter $\lambda$ is when the decision making is very important or decision time is high, $\lambda$ can be set as high as possible like $\lambda = 0.9$ or higher one; otherwise, when decision cost is high or decision time is limited, the $\lambda$ can be set as lower value like $\lambda = 0.8$ or below that. And therefore, in this study, we are focused to achieve the consensus level without paying attention to the determination of the threshold.

#### 2.1.1.4 Feedback Mechanism

In general CRP framework, the main aim of the feedback mechanism is to generate the preference modification advice for the DMs in order to reach an acceptable consensus value. This phase aims to support the DMs to achieve the higher consensus level, which is often facilitated by the identification and direction rule [26], [27].

**a). *Identification rule:*** It is used to identify the inconsistent DM(s), with the lower consensus degree using Eq. (2.3).

**b). *Direction rule:*** It is used to recommend changes to the identified inconsistent DM(s) to get close to the group preference $V^c$ with the aim of increasing the level of consensus and consequently the group consensus degree. The direction rules for recommending DMs for adjusting preferences $\overline{v}_{ij}^{p}$ obeys the following rules:

$$\begin{cases} \overline{v}_{ij}^{p} \in [min(v_{ij}^{p}, v_{ij}^{c}), max(v_{ij}^{p}, v_{ij}^{c})], & i \geq j \\ \overline{v}_{ji}^{p} = 1 - \overline{v}_{ij}^{p} \qquad , & i < j \end{cases} \tag{2.4}$$

Once all the DMs modify their preferences according to the recommendation provided in Eq. (2.4), the new group preference matrix $\overline{V}^{c} = (\overline{v}_{ij}^{c})_{n\times n}$ can be determined. If the consensus among the DMs is achieved, the group preference relation $\overline{V}^{c}$ is used to find the rank of the alternatives. This is done by associating the group preference value $Q_i$, to each alternative $x_i$. Various methods have been suggested to obtain $Q_i$, such as row averaging method and ordered weighted average (OWA) operator [19]. Here, in this study, the row averaging operator is used to calculate $Q_i$, i.e.,

$$Q_i = \sum_{j=1}^{n} \overline{v}_{ij}^{c}/n\,, i = 1, 2, \ldots, n \tag{2.5}$$

The obtained value $Q_i$ can be interpreted as the dominance of alternative $i$ over the rest of the alternative [28]. The higher the evaluation value $Q_i$, the higher the rank of the alternative $x_i$ over the set of the alternatives.

### 2.1.2 Bounded Confidence

The bounded confidence model defined in the discipline of opinion dynamics defines the willingness of the individuals in refereeing the opinions of the others [29]. In this model, a decision maker will only take into account the opinion of others if that differ from its own opinion not more than a certain confidence level, which is described in brief below:

Let $V_p = \left(v_{ij}^{p}\right)_{n\times n}$ be the expressed opinion of a decision maker $d_p$ and let $V_a = \left(v_{ij}^{a}\right)_{n\times n}$ be the assigned advice to the decision maker and $\sigma_p \in [0,1]$ be his/her bounded confidence. Then, the provided advice $V_a$ will be accepted by the decision maker $d_p$ only when its distance $D_{pa}$ is smaller than $\sigma_p$, i.e.,

$$D_{pa} \leq \sigma_p \tag{2.6}$$

where $D_{pa} \in [0,1]$ computed as follows:

$$D_{pa} = \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left|\left(v_{ij}^{a} - v_{ij}^{p}\right)\right|}{n.(n-1)/2} \tag{2.7}$$

### 2.1.3 Blockchain

Blockchain can be defined as a decentralized database widely used for recording transactions. It is a distributed database that maintains the list of records as a transaction in tamper-resistant form. Each participant of the blockchain stores a full copy of the blockchain, thus preventing it from a single point of failure. Typically, it consists of a series of blocks containing the transaction data. Each block contains the hash value of the previous block for the connection. The linkage mechanism ensures the reliability of the blockchain, and thus any modification in the data is not possible once written to the blockchain. A block is called validated in the blockchain when multiple parties verify it. Furthermore, the transactions, also called data in the block, cannot be modified arbitrarily.

The advent of blockchain 2.0 [30], which introduced smart contracts, facilitates the application to run without a trusted third party. A smart contract is "*a digital contract that is written in source code and executed by the computers, which integrates the tamper-proof mechanism of blockchain*" [31].

Ethereum blockchain is an open-source, public blockchain that helps us create a protocol for building decentralized applications. Ethereum does this by allowing to write a smart contract, which is a set of rules that gets executed only when certain conditions are met. In Ethereum, the accounts owned by the smart contracts are considered internal accounts that can interact among themselves, and with that, the external account owned by the system's users [32]. The execution of a smart contract is triggered via transaction. The participants who execute the transactions are charged a fee called gas cost to use computational resources on the network. Gas cost is measured in terms of Wei, the smallest unit of ether, which is the native cryptocurrency of Ethereum. Despite providing the participants with some economic incentives, the gas cost prevents malicious participants from clogging the network by asking for infinite computational resources. Due to the immutable characteristic of blockchain, the smart contract, once deployed, cannot be modified. Hence, the participants who agree to its code are sure there is no possibility of a breach. As per the facilities provided by the smart contract in Ethereum, several works find many application domains in healthcare, supply chain, Internet of Things, etc. [32].

In combination with smart contracts, Blockchain can provide the properties like reliable delivery of messages, account address, and transparent third-party platform [33]. Unlike the conventional systems, several characteristics of Blockchain which distinguish it from others and bring an imperative platform for dealing in real life are as follows:

***Decentralization:*** The core concept and benefit of blockchain is its decentralized nature, which means no trusted third party is involved in validating the transactions. Instead, each node can use the consensus mechanism to validate the transactions. Also, the whole blockchain is maintained by each node.

***Immutability:*** It is nearly impossible to change the data once stored in the Blockchain. It is not truly immutable, but since tempering the transaction is a difficult and time-consuming process, it is seen as a benefit to maintaining an immutable ledger of transactions. Thus, we can say that the data in the distributed ledger is highly immune to any tempering.

***Anonymity of Users' Identity:*** As soon as the participant gets registered to the blockchain network, they are provided with public and private keys. Since the transactions are done only by using the public key, it is tough to track the real identity of the participant.

***Auditability:*** The auditability property of Blockchain derives from the immutability and transparency properties. In the Bitcoin blockchain, an Unspent Transaction Output (UTXO) model stores the users' balance information. Each transaction is supposed to specify the previous unspent transactions. The miners validate the transactions to check if these mentioned transactions are unspent.

***Transaction verification:*** Any transaction generated or posted by a node in a blockchain network is first verified based on a predetermined set of rules. Only valid transactions are included in a block.

***Non-repudiation*****:** Digital signature is used in blockchain to achieve non-repudiation. Transactions in blockchain incorporate digital signature of sender, therefore sender cannot deny its transaction.

***Security assurance:*** With the combination of popular security techniques like hash function, Merkle tree, digital signature, and consensus mechanism, the Blockchain can stop modifying any transaction data in the block after successfully committing to the Blockchain. For a blockchain to function with security and privacy concerns, efficient and secure consensus algorithms are used, ensuring that the nodes hold an identical chain of blocks without relying on the central authority. It protects the system from malicious adversaries from disrupting the main server. The most used consensus algorithm is the proof of work that is considered unsafe only when 51% of the computational power is controlled by one node, which is hard to achieve.

## 2.2 Literature Review

In this section, we study the existing CRPs designed to solve various GDM problems for the purpose of performing the literature survey and thereby identifying the issues in the existing CRPs. For the purpose of studying the existing CRPs, this thesis identifies some key aspects often involved in the consensus process based on soft consensus: heterogeneity of DMs, feedback mechanism, unavailability of DMs, and the GDSS (Group Decision Support Systems). Out of all the CRPs discussed in the literature, regarding the main aspects of focus in the CRP study, we reviewed the CRP literature based on these key aspects. While doing the literature review, we divide the existing CRP methods into four categories: CRPs for heterogeneity of the DMs, CRPs for feedback cost, CRPs for unavailability of DMs, and CRPs for security and trust issues.

### 2.2.1 CRPs for Heterogeneity of DMs

In literature the problem of heterogeneous GDM is defined in three categories [34]. The very first framework of heterogeneous GDM is related to the different preference formats. In this framework, the DMs express their opinion using different preference relations such as multiplicative preference relations, fuzzy preference relations, utility functions and preference orderings [35]–[40]. The second most heterogeneous framework in GDM emerges when the involved DMs hold different levels of knowledge and understanding concerning the problem at hand [41], [42]. In certain cases, the DMs have different labels to judge preferences based on the multigranular and unbalanced linguistic contexts [43][44] which also falls in the second category of defined heterogeneity in GDM. The third last framework looks into the varying expressions of DMs, highlighting their individual preferences with respect to the attributes of each alternative considered. It offers about the attributes defining the alternatives, which not only takes up crisp or uncertain information, but also includes the fuzzy numbers, linguistic data or interval numbers. For instance, to aggregate the fuzzy weights in GDM, Chou *et al.* [52] introduced a fuzzy simple additive weighting system, but heterogeneity among the DMs was not considered in the aggregation or consensus state. Similarly, there are several other methods developed to deal with the heterogenous GDM problems but they are limited to the extent of heterogeneous information. These methods do not consider the heterogeneity in context of DMs.

For heterogeneous DMs based GDM problem, there has not been much discussion in the literature of GDM. Perez and Cabrerizo [34] pointed out the idea of non-homogeneous DMs. They assumed that the DMs with deeper knowledge as the main leaders of the negotiation and gave high importance to them. This idea found its frontier more in dealing large scale GDM [45]. Recently, Tang and Liao [46] discussed the heterogeneous decision-making where they categorized the DMs as independent and non-independent. However, the aforementioned studies of heterogeneous DMs explore the types of DMs just from point of knowledge and expertise and seldom consider the case when the DMs might have unstructured knowledge accumulated through their experiences, which may affect the acceptance of the final decision result. However, there are situations where some of the decision-makers may not be interested in receiving the feedback recommendations. In such a heterogenous DMs context, it could be adequate to use them as resource persons to help experts bring out the wise decision.

In the past few years, the traditional decision-making approaches have been great in providing services to practical decision problems. Different GDM models, including several experts as decision-makers, have been proposed in the literature [47][6]. However, with the rapid development of information and communication technology, the decision context has become more complex. The development of new communication channels like social networks, individuals are more interested in participating in the decision-making process. A model that relies on experts' opinions lacks such support and assistance in decision-making. For example, in socio-technical systems such as smart cities [48], the input from the citizens defines the dynamics of the city. Citizens play an important role in the development of the smart city as they are the users, consumers, decision-makers and data and information producers [49]. As citizens know their local communities better than anyone else, their opinions help the government respond to evolving situations and implement changes that are in the public's best interest. Whether it is public policy decision-making or participatory budgeting [50], the non-elected citizens are involved in the decision model. Similarly, the end-users of the service provide their preference according to their good or bad experience. There are experts who conclude from the end-user's feedback. This way, the experts gain insight into the valued social settings, which are usually overlooked. In turn, the decision-making organizations improve the legitimacy and transparency of the decision-making. Therefore, their opinions, if not considered in the decision-making process, can negatively impact the city, such as the implementation of unpopular policies. This challenges the traditional decision-making approaches where the city officials, government representatives, system experts etc., were supposed to be the only DMs.

Thus, it becomes necessary to embrace the new ideas and advice of the citizen as an input to decision-making problem that truly benefits all concerned [51]. In this thesis, such potential actors of the society who know their local communities better are called as the non-experts. This way, collective intelligence across different subgroups of society can be leveraged simultaneously, involving experts and non-experts, called heterogeneous DMs [46] in this study.

### 2.2.2 CRPs for Feedback Cost

One critical issue in CRP is the generation of feedback recommendations for the inconsistent DMs to improve the consensus among DMs. The feedback mechanism plays a vital role in CRP since it facilitates DMs in consensus building. In particular, there are two types of feedback mechanisms: (i) The identification and direction rules [6], [27], (ii) optimization based consensus rules [52], [53]. The interactive feedback mechanism also called as identification and direction rules based (IR-DR) [6][27], pays attention to the intervention of the DMs that respect the DMs opinions whereas the automatic process on the other hand automatically updates the DMs opinion. The first rule identifies the inconsistent DMs and suggests them with the adjustment advice. Several researchers used the feedback mechanism based on IR-DR rules so as to help DMs reach an acceptable consensus level. In different context and for different purposes the IR-DR rules-based feedback mechanism is used. Zhang and Guo [54] proposed identification and direction rule-based consensus model that implemented individual consistency rules. Herrara-Viedma et al. [26] used the identification and direction rules to build the consensus in GDM with multi-granular linguistic preference relation. Wu et al. [55] applied the feedback rule to facilitate consensus in social network GDM with trust propagation. A democratic consensus reaching process (DCRP) for MpMcLSDM (Multi person multi criteria Large Scale Decision Making) is proposed in [56] where a compromise degree-based consensus feedback method is developed. Focusing on providing the adjustment advice to the DMs based on the first rule, Zhang and Guo [54] proposed an identification and direction rule-based consensus model that implemented individual consistency rules. Mata et al. [26] used the identification and direction rules to build the consensus in GDM with multi-granular linguistic preference relation. In contrast, Wu et al. [55] applied this feedback rule to facilitate consensus in social network GDM with trust propagation. However, these existing feedback mechanisms focus on generating the feedback recommendation based on the voluntarily selected feedback parameter. Depending on the feedback parameter selected, the number of rounds to reach consensus may vary which can be time-consuming also which is also a major challenge in designing the feedback process [52].

The second type, minimum adjustment and cost rules [52], aims to minimize the adjustment and cost while reaching a consensus. Optimization-based consensus rules generate optimal adjusted preference values that DMs can utilize to modify their own preferences and make better informed decisions. Zhang et al. [57] used the minimum adjustments in the feedback process to propose the 2-rank CRP in a multi-granular linguistic context. In the multicriteria decision problem, Ben-Arieh and Easton [58] used minimum cost consensus, and Wu et al. [59] utilized the minimum cost consensus model in social network GDM. Considering that the adjustment cost is usually associated with the consensus process [9][60][61], Wu et al. [59] proposed a minimum cost optimization model to help experts achieve the consensus threshold subject to cost constraint. Thus, the minimum adjustment and cost rules focus on the feedback mechanism to identify the inconsistent experts, alternatives or preferences and provide feedback with minimum adjustment costs.

To show the validity of the feedback mechanism, Wu and Chiclana [62] proposed a visual feedback mechanism by presenting the graphic representation of the consensus state in each round of feedback. Depending upon the current consensus state of the DMs, the personalized feedback mechanism is proposed in [63]. The aim is to generate advice with less adjustment opinion for the individual closer to the group opinions while more adjustment to those farther from the group opinion. Further, Cao and Wu [64] proposed a personalized feedback mechanism facilitating experts to select the individual feedback parameters to reach a consensus. The study focusing on generating personalized feedback to the DMs are also less suitable for achieving consensus at once.

After studying several existing CRPs using different feedback mechanism [54][55][65][66][59][62][56] etc., we find that no CRPs have been designed with the aim of achieving consensus at the earliest. There are situations like emergency events such as health emergency or natural disasters, where decision-making need to be made in limited time. The emergency events take place unexpectedly and hence the decisions need to be taken in as early as possible despite having the poor information [67]. Thus, to model an effective and efficient feedback process for building CRP providing decision in a limited time is an important issue. Though the discussed feedback mechanisms have been widely accepted among the researchers, it iteratively adjusts the individuals' opinion until the consensus is reached and thus becomes a time-consuming process. It. This in turn incurs a huge cost in the decision-making process. According to Zhang et al. [52], the number of iterations to reach consensus is one of the criteria for measuring consensus efficiency. Hence the consensus efficiency can be improved by providing a constant number of feedback advice, minimizing the cost. As stated above, there are studies on improving the feedback cost though, the consensus efficiency is still a problem to address. In most cases, the inconsistent DMs, after adopting the generated advice, have no idea of their consensus status [68]. Because of this, DMs may show non-cooperation towards the acceptance of the provided feedback, which could result in a lack of willingness to the adjustment of the original preference [65][66][59]. However, reaching consensus requires negotiation rounds which is to be implemented by the feedback mechanism. This incurs a challenge in the design of a feedback mechanism that helps build consensus with minimal rounds of discussion and thereby minimizing the cost to reach consensus. We here call this as feedback cost that needs to be addressed for the sake of developing CRP for situations where there is limited time and decisions are required as early as possible. To the best of our knowledge, only a few studies focus on the research of this issue where decision-making need to be made as early as possible.

### 2.2.3 CRPs for Unavailability of DMs

The literature discusses the CRPs with a focus on several aspects of GDM. There are CRPs, discussed for different representations of preference structures [69][70], CRPs in social network [71], CRPs in web/dynamic context [72], CRPs for consensus/consistency [54][73], CRPs for behaviors and attitudes of DMs [74], [75] and so on. These models provide recommendations to the DMs on how they form the consensus, how to increase the consensus among the experts [7][10], how a change in their opinion would influence the degree of consensus [34] and how to reach consensus in web/dynamic context. The main common assumption in all such GDM models is the fixed set of DMs participating into the decision process that are static throughout the process. However, due to technical and non-technical reasons, some of the DMs cannot be continuously available. Unavailability at times may be there because of technical reasons like network failure or the non-technical reasons like personal, sociological, organizational and hence the various patterns of unavailability could be observed. Thus, to make the quality and a mature decision incorporating the opinions of the complete group of DMs at a given time, a decision-making framework is required. Therefore, it is necessary to address the problem of unavailability of DMs or partial availability in the active decision-making process. The literature of GDM addresses the similar problem where the DMs can leave and join the decision-making process throughout the process. In the extant literature, Molinera *et al.* [76] and Perez *et al.* [77] investigated the dynamic set of DMs under the dynamic environment for decision making. Recently, [76] proposed a consensus model for addressing the multi-criteria group decision making events that are handled by allowing new DMs to join in-between the process while the existing DM can abandon the process. Some researchers implemented a delegation mechanism for LSGDM problem and for heterogenous GDM problem where the exit delegation mechanism discussed in Xu *et al.* [78] advice the DMs lower than the expected agreement level to exit the decision-making process. This helps reach consensus quickly. Not only this the exited DMs give trust weight to the other DMs through the delegation mechanism. Thus, preserving the influence of exited DMs too into the decision-making process. Tang *et al.* [46] developed GDM model where the role of a group of DMs called as external ones is just to provide opinions at once and exit the process. A delegation mechanism is discussed in the GDM proposed in [46] to provide trust weight to the internal DMs by the external DMs. Although these approaches found to be very useful dealing with the dynamic decision making environment, they still need to be further improved to cope with availability of the given number of DMs throughout the decision process because (1) in the works of [76][77] the same DM joining the discussion after being unavailable for one or more rounds of discussion is considered as a newly joined DM and (2) the management of the dynamic set of DMs is considered to be heavily flexible with no credence given to the most available experts.

### 2.2.4 CRPs for Security and Trust Issues

A Decision Support System (DSS) [79] supports the DMs in solving their decision problems. The DSS provides a negotiation platform that enables DMs to make group decisions, which is often called as Group DSS (GDSS). A GDSS indicate those software applications who's main is aim is to facilitate DMs to make appropriate choices when facing decision situations. DMs provide their opinions and receive feedback recommendations through the GDSS and thereby leading to a digital exchange of data. Several GDM support systems have been found in the literature review such as LaSca [80], which provides flexibility in which the DMs can "decide on how to decide", MENTOR [81], a graphical tool that studies the evolution of the preferences during the GDM process and DeciTrustNet [82] which usually takes into account the trust and reputation in the social networks. However, this support system adopts the traditional models, in which GDSS is fully controlled by an administration. The centralization of GDSS platform may result in a number of issues such as vulnerability to single point failure, security and privacy risks [83], [84]. In addition, the GDSS platform needs to deal with the tampering of the preference information which may cause the unfair final result since the GDSS might get biased toward a certain alternative. Though these systems have been in place for a long time, now everyone wants the control of their own data and privacy, the things which the decentralized can provide us with which the centralized systems cannot. Thus, a decentralized system with no single party owing the complete network is the alternative solution. However, implementing a decentralized GDSS in an untrusted environment is a challenge. Fortunately, recently emerged blockchain technology can provide a trusted environment for developing decentralized GDSS, addressing the issues of centralized GDSS. Blockchain with a decentralized nature can provide immutability, security and transparency without a central authority. Therefore, it can be considered a potential approach to encouraging the individual's consciousness in participatory decision making. Blockchain provides a unique address for each registered account, using which the transactions are performed instead of real identity to preserve an individual's privacy. Blockchain is applied to design various decentralized platforms like cloud exchange [85], service selection [86], social applications [87] and smart cities [88] to utilize its benefits. Ethereum blockchain providing the feature of smart contract, popularly used to design decentralized systems, lashes out the possibility of censorship, trust issues or third-party dependence [89].