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Title: Handling dynamic group decision making processes with high number of alternatives using interval type-2 hesitant Fuzzy Ontologies and sentiment analysis

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Abstract: The high spread of Internet and social networks have completely changed the way that Group Decision Making methods are carried out. Experts are now involved in environments where a large amount of information is available and new ideas and participants can appear at any time totally changing the decision environment. In this paper, a novel group decision making method for dynamic contexts that have a high number of alternatives is presented. A perceptual computing scheme is used in order to extract information from the experts. It uses sentiment analysis over the debate texts in order to obtain information for selecting the best alternatives on each round. Moreover, interval type-2 hesitant Fuzzy Ontologies are used in order to store the alternatives related information in an organized way. By using interval type-2 and hesitant fuzzy sets, imprecise information can be represented in a comfortable and intuitive way on the ontology.

19/11/2019

Dear Editor,

I am writing this cover letter for the submission of our manuscript entitled “Handling dynamic group decision making processes with high number of alternatives using interval type-2 hesitant Fuzzy Ontologies and sentiment analysis” for consideration for publication in “Knowledge-Based Systems” journal.

The main goal of our work consists in designing a novel Group Decision Making model that employs fuzzy ontologies and sentiment analysis in order to deal with high number of alternatives. Sentiment analysis is employed in order to extract the characteristics that the experts consider that a good alternative should have. This is made directly over the transcriptions of the texts used in the debate that the experts have carried out. This way, experts do not have to provide any information to the system in this step. Afterwards, using the obtained information, a reduced set of alternatives is extracted from a fuzzy ontology that contains information about all the alternatives. Finally, a Group Decision Making process is carried out using this reduced set of alternatives. In order to improve the flexibility of the information representation, a novel model of fuzzy ontology is presented. Instead of using fuzzy sets, interval type-2 fuzz sets are used for representing the information. Thanks to it, a more flexible information representation tool is designed.

This manuscript describes original work and is not under consideration by any other journal. All authors approved the manuscript and this submission.

Thank you for receiving our manuscript and considering it for review. We appreciate your time and look forward to your response.

Best regards

Juan Antonio Morente-Molinera et al

Dear reviewers and editor,

Thank you very much for your useful comment, they were really appreciated. In this new version of the paper, we have improved the paper according to all your suggestions. The novelties of the method have been more clearly stated. The rest of reviewer comments have also been answered and the paper has been rewritten accordingly.

We really appreciate the hard work and the time that all of you have spent reviewing this article.

Detailed answers to all the reviewers' suggestions can be found below.

Reviewer 1

Point 1

Many language errors are spotted in the manuscript, such as 'fuzzy ontologies for thispurpose' without space, 'the sentiment of the user as expressed in a piece if text', 'Recent contributions focusing on perceptual includev...' and so on.

Answer: Thanks for the comment. This and other typos have been fixed.

Point 2

Some incorrect display could be found in the figures, such as Figure 3.

Answer: The display has been fixed in order for the text to be shown at a good size.

Point 3

The novelty of the paper needs to be addressed. In the current form, the contribution is only mentioned in the Discussion session, where it is stating that (1) the other GDM papers fail to consider large amount of information, (2) the set of alternatives could be updated in each round, (3) the papers do consider large amount of information fail to use fuzzy ontologies, and (4) the papers only focus on the high number of experts leaving criteria. However, for contribution (1) and (4), the cited work(23) which is also written by the same authors did consider large amount of information in terms of alternatives and participants(experts). Actually, in both the decision making steps and the numerical example,

Point 3.1

the multi-round of GDM has not been illustrated clearly, after reading the paper, it is still quite unclear when and how to define a round, since the experts can come and go at any time spot.

Answer: Thank you for your valuable comment. The part of the paper that mention that feature has been rewritten in order to clarify how the inclusion and removal of the experts influence the actual Group Decision Making round. Some information has also been added to the introduction section.

New text in the method description section:

- **Modifying the set of experts**: At any time of the process, any expert can join or leave. When an expert abandons the process, his/her preferences are deleted from the system and the ranking needs to be recalculated using only the texts of the remaining experts. Therefore, the actual GDM round stops and the GDM process goes back to the *generating the reduced set of alternatives* step depicted in subsection 3.3. The reduced ranking of alternatives is recalculated and the process continues from there. New experts can also join the debate at any time of the process. In this case, the actual GDM round stops and it goes back to the *extracting information from the debate of experts* step depicted in subsection 3.2. The debate on the characteristics is restarted and the new experts share their opinion with the ones that were there before. The process continues from there as usual.

New text on the introduction section:

- **It works on dynamic contexts**: The designed GDM process allows experts and alternatives sets to be modified at any time. The information that the experts are analyzing and the availability or adequateness of including them in the process may change. Therefore, it is important to design GDM methods where the set of alternatives and experts may vary. If a designed GDM method is not capable of adapting itself to real world problems where the information is constantly being updated and where the decision setting can change, then it cannot be correctly employed.

Point 3.2

As for the distinction of the present paper against the existing ones, the contribution (3) is rather weak given only the crisp number is substituted by fuzzy ontologies.

Answer: Thanks for the comment. New text has been added in order to emphasize the novelty of the method. It has been included in the introduction and in the discussion section. Some text focusing on why the presented method is superior to the one presented in (23) is also included.

New text on the introduction section:

The presented methodology is novel and innovative due to the fact that it includes the following features:

- **Information is extracted directly from debate texts**: By using sentiment analysis, the information for reducing the initial set of alternatives is obtained directly from the transcriptions of the debate texts. This entails two different advantages. First, the number of interactions that experts make with the computational system is reduced making the process easier for them. Second, they can express themselves in a comfortable way using free text which is how they usually communicate.

- **Hesitant fuzzy ontology is used for storing alternatives related information**: In most of the cases, the information that is stored on the fuzzy ontology is quite imprecise. In this paper, a novel fuzzy ontology design which uses type-2 hesitant fuzzy sets is presented. They allow the fuzzy ontology to store the information in a more flexible way. For instance, several labels can be assigned when describing how an alternative fulfills a specific characteristic.

- **It is designed for working with a high number of alternatives**: Thanks to fuzzy ontologies, it is possible to carry out GDM processes that have a high number of alternatives. By performing queries, experts can focus on the most promising alternatives. Also, the information that is related with the alternatives, which can be also quite high, is correctly managed by the fuzzy ontology. Thanks to this, experts must only focus on deciding which are the better criteria leaving to the fuzzy ontology the task of deciding which alternatives fulfill it.

- **It works on dynamic contexts**: The designed GDM process allows experts and alternatives sets to be modified at any time. The information that the experts are analyzing and the availability or adequateness of including them in the process may change. Therefore, it is important to design GDM methods where the set of alternatives and experts may vary. If a designed GDM method is not capable of adapting itself to real world problems where the information is constantly being updated and where the decision setting can change, then it cannot be correctly employed.

New text on the discussion section:

Although in [32], the described method works with high number of alternatives and experts, it does not consider any information related to the alternatives. Therefore, experts must find this information and get an idea about how to rank them on their own. In our new method, fuzzy ontologies help the experts to carry out an organized debate by managing all the alternatives related information. It is important to include tools that allow experts to manage all the alternative related information because, specially in environments where there is a high number of alternatives, experts can get lost among all the available data. This can lead to poor decision results due to the incapability of the experts to process all the information on their own.

It is also important to notice that there is little research on the application of sentiment analysis over GDM methods that employ tools to manage high amounts of information. Thanks to sentiment analysis, there is no need of an extra step where the experts have to explicitly provide the desirable characteristics of the alternatives to the system. This information is directly obtained from the debate. Also, this feature allows experts to share information in common language making the process much more comfortable for them. It should be noticed that improving human-computer communication and reducing the number of actions that experts must perform is critical in order to design GDM methods that correctly works in complex environments where participants may get lost due to the high amount of information that they have to deal with. Neither of the previous methods include this feature.

Point 4

The title of the paper is not succinct and hard to follow.

Answer: The title has changed to "A dynamic group decision making process for high number of alternatives using hesitant Fuzzy Ontologies and sentiment analysis".

Point 5

The sentiment analysis is mentioned in the title as well as Subsection 2.2, however, the way to implement the analysis has not been demonstrated in the following sections.

Answer: Thanks for the suggestion. Section 3.2 has been rewritten in order to better connect to subsection 2.2. The reader can now better identify where sentiment analysis is applied.

New text:
The debate can be initiated once that the fuzzy ontology is constructed. Experts can use a social network or an online forum. In order to obtain the most desirable characteristics for the alternatives from the transcriptions of the debate, sentiment analysis procedures are employed. In this paper, the bag of words sentiment analysis approach depicted in subsection 2.2 will be used. In order to carry out this process, the next steps are followed:

- **Defining lists of positive and negative words**: In the sentiment analysis bag of word approach, several lists of sentiments' related words must be generated in order to track the desired postures. Since our method is tracking opinions, a list of positive and negative words will allow us to identify positive and negative feelings on the alternatives.
- **Classifying the texts according to the alternatives characteristics**: Each concept has an associated keyword list, kw_i that contains words that unambiguously identify the concept. Using this list, one can identify the concept that is mainly referred by each text by analysing the debate transcriptions. Based on this analysis, the system can create the indexed family T, defined as

$$T = \{t_{ij}\} | c_i \in C, e_j \in E$$

  Where t_{ij} is a set of texts provided by e_j that mention how the c_i should be fulfilled by the alternatives.
- **Searching for positive and negative words in the texts**: Once the classification is performed, words from the positive and negative lists can be searched for in order to determine the desirable characteristics. Thanks to this, it is possible to identify how the experts were feeling when writting each of the texts. For each expert and concept, values $pwcount_{ij}$ and $nwcount_{ij}$ are calculated. They indicate, respectively, the number of times that positive and negative words have been provided by the experts when the characteristic c_i was being mentioned by e_j. Positive words indicate that the expert values positively the characteristic since he/she has positive sentiments about it. On the other way around, negative words indicate that the expert does not like it.
- **Calculating the preference value for each expert and characteristic**: Once that the sentiment analysis procedure have been performed, it is possible to use the pwcount and nwcount values for calculating a numerical value, p_{ij}, that indicates the level of fulfillment that the alternatives should have about an specific concept:

Reviewer 2

Point 1

The novel; contribution of the paper is not clear, it need major revision demonstrating what is the main contribution in comparison with the recent state of art,

Answer: Thanks for the comment. New text has been added in order to emphasize the novelty of the method. It has been included in the introduction and in the discussion section.

New text on the introduction section:

The presented methodology is novel and innovative due to the fact that it includes the following features:

- **Information is extracted directly from debate texts**: By using sentiment analysis, the information for reducing the initial set of alternatives is obtained directly from the transcriptions of the debate texts. This entails two different advantages. First, the number of interactions that experts make with the computational system is reduced making the process easier for them. Second, they can express themselves in a comfortable way using free text which is how they usually communicate.
- **Hesitant fuzzy ontology is used for storing alternatives related information**: In most of the cases, the information that is stored on the fuzzy ontology is quite imprecise. In this paper, a novel fuzzy ontology design which uses type-2 hesitant fuzzy sets is presented. They allow the fuzzy ontology to store the information in a more flexible way. For instance, several labels can be assigned when describing how an alternative fulfills a specific characteristic.
- **It is designed for working with a high number of alternatives**: Thanks to fuzzy ontologies, it is possible to carry out GDM processes that have a high number of alternatives. By performing queries, experts can focus on the most promising alternatives. Also, the information that is related with the alternatives, which can be also quite high, is correctly managed by the fuzzy ontology. Thanks to this, experts must only focus on deciding which are the better criteria leaving to the fuzzy ontology the task of deciding which alternatives fulfill it.
- **It works on dynamic contexts**: The designed GDM process allows experts and alternatives sets to be modified at any time. The information that the experts are analyzing and the availability or adequateness of including them in the process may change. Therefore, it is important to design GDM methods where the set of alternatives and experts may vary. If a designed GDM method is not capable of adapting itself to real world problems where the information is constantly being updated and where the decision setting can change, then it cannot be correctly employed.

New text on the discussion section:
Although in [32], the described method works with high number of alternatives and experts, it does not consider any information related to the alternatives. Therefore, experts must find this information and get an idea about how to rank them on their own. In our new method, fuzzy ontologies help the experts to carry out an organized debate by managing all the alternatives related information. It is important to include tools that allow experts to manage all the alternative related information because, specially in environments where there is a high number of alternatives, experts can get lost among all the available data. This can lead to poor decision results due to the incapability of the experts to process all the information on their own.

It is also important to notice that there is little research on the application of sentiment analysis over GDM methods that employ tools to manage high amounts of information. Thanks to sentiment analysis, there is no need of an extra step where the experts have to explicitly provide the desirable characteristics of the alternatives to the system. This information is directly obtained from the debate. Also, this feature allows experts to share information in common language making the process much more comfortable for them. It should be noticed that improving human-computer communication and reducing the number of actions that experts must perform is critical in order to design GDM methods that correctly works in complex environments where participants may get lost due to the high amount of information that they have to deal with. Neither of the previous methods include this feature.

Point 2

Please cite the below references and provide some relative closeup to have better comprehension on the related research state.

-"A multiple attribute decision making three-way model for intuitionistic fuzzy numbers", International Journal of Approximate Reasoning, Volume 119, April 2020, Pages 177-203

1-"A New Representation of Intuitionistic Fuzzy Systems and Their Applications in Critical Decision Making" IEEE Intelligent Systems https://doi.org/10.1109/MIS.2019.2938441

2-"Fuzzy Group Decision Making for influence-aware recommendations", in Computers in Human Behavior, Volume 101, December 2019, Pages 371-379 https://www.sciencedirect.com/science/article/pii/S0747563218305363

3-"Successes and challenges in developing a hybrid approach to sentiment analysis", Applied Intelligence, Springer, May 2018, Volume 48, Issue 5, pp 1176-1188

4-"A visual interaction consensus model for social network group decision making with trust propagation", Knowledge-Based Systems, Volume 122, 15 April 2017, Pages 39-50

5-"Hesitant Fuzzy Linguistic Preference Utility Set and Its Application in Selection of Fire Rescue Plans," International Journal of Environmental Research and Public Health, 2018, 15(4), 664; http://www.mdpi.com/1660-4601/15/4/664

6-"Fuzzy Group Decision Making with Incomplete Information Guided by Social Influence", IEEE Transaction on Fuzzy Systems, Volume: 26, Issue: 3, June 2018, pp. 1704-1718

7-Hypotheses Analysis and Assessment in counter-terrorism activities: a method based on OWA and Fuzzy Probabilistic Rough Sets" : IEEE Transactions on Fuzzy Systems, https://doi.org/10.1109/TFUZZ.2019.2955047

8-"Fuzzy Rankings for Preferences Modeling in Group Decision Making," International Journal of Intelligent Systems, Volume33, Issue7, July 2018, Pages 1555-1570

Answer: Thanks for the comment. The state of the art of the paper have been updated as suggested.

New text:

In [23], intuitionistic 2-tuple linguistic label sets are used for dealing with multi-attribute GDM environments. In [39], authors present a novel representation for intuitionistic fuzzy systems that they apply on Critical Decision Making. In [7], GDM environments where experts' influence is used to generate recommendations are introduced. In [50], trust propagation among the experts is used in order to develop a visual consensus model for GDM methods that are carried out on social networks. In [5], a method that estimate missing preferences using social influence among the experts is presented. In [6], fuzzy rankings are used in order to rank alternatives in GDM environments. In [24], a three-way decision approach that uses intuitionistic fuzzy sets is used to solve multi-attribute decision making problems. In [21], a linguistic scale function that transforms the semantics corresponding to hesitant linguistic terms into the linguistic

preference values is proposed. The presented methodology is applied on fire rescue plans. In [51], fuzzy probabilistic rough sets and probability theories are uses in order to assist decision makers in the analysis of intelligent information coming from terrorist groups.
…
In [1], successes on developing a hybrid sentiment analysis and future challenges are depicted.

Point 3

Some minor errors are depicted below.
Line 9 on Page 3 out of 34 total pages
Please change "result in increased number of" to "result in an increased number of".
Line 23 on Page 3
Please change "for thispurpose [39]" to "for this purpose [39]".
Line 16 on Page 5
Please change "In practice, Pk typically" to "In practice, Pk is typically".
Line 5 from the bottom on Page 5
Please change "the rpocess" to "the process".
Line 7 after Figure 2 on Page 7
The spelling of "perceptual includev" is incorrect. Please change it.
Line 3 after Figure 3 on Page 8
Please change "are increasingly present" to "are increasingly presented".
Line 15 on Page 24
Please change "dealing with high number of" to "dealing with a high number of".

Answer: All the commented typos and some others have been fixed.

A dynamic group decision making process for high number of alternatives using hesitant Fuzzy Ontologies and sentiment analysis

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Abstract

The high spread of Internet and social networks have completely changed the way that Group Decision Making methods are designed, developed and implemented. Experts now operate in environments where a large amount of information is available and new ideas and participants can appear at any time; this results in a dynamically changing decision environment. In this paper, a novel group decision making method for dynamic contexts with a high number of decision alternatives is presented. As the main component of the proposal, a perceptual computing scheme is used in order to extract information from the experts. In the process, sentiment analysis is used when analysing the debate texts in order to obtain information for selecting the best alternatives on each round. Moreover, interval type-2 hesitant Fuzzy Ontologies are used in order to store the information related to alternatives. By combining interval type-2 and hesitant fuzzy sets, imprecise information can be represented in a comfortable and intuitive way within the ontology.

Keywords: Group Decision Making, Fuzzy Ontologies, Sentiment analysis, Computing with words, Type-2 hesitant fuzzy sets

1. Introduction

Group Decision Making (GDM) as a field has gained significant and continuously increasing attention since its first appearance in the early 80's [9] until recently [18, 33, 36]. The recent growth in Internet usage, generated information and the appearance of social networks [48] have provoked a change in the way that GDM processes are designed and implemented. This new environment generates several challenges that are not handled appropriately by existing models. Some of the important challenges that motivated the proposal presented in this article include the following:

- **Large number of alternatives**: with the information explosion in the present digital age, the increased amount of generated insight result in an increased number of recognized decision alternatives. When facing a large number of alternatives, experts in a group can have more difficulties when trying to reach an agreement. Therefore, there is a need of developing tools that aid the experts to deal with this overload of alternatives. Some references that deal with this topic include [27, 36, 42].

- **Large amount of information about each alternative**: in theory, the more information an expert acquires on an alternative, the more informed the resulting decision should be as weak and strong points of individual alternatives can be easily recognized. However, beyond a limit, the amount of information related to the alternatives that the experts have to deal with would be quite difficult to manage. In order to solve this issue, it would be desirable to employ a tool capable of storing and organizing the information in an optimized way. One possible option is the use of fuzzy ontologies for this purpose [49]. Fuzzy Ontologies can provide the experts with a reduced set of alternatives that they can discuss about and information about the desirable characteristics of the alternatives can be directly extracted from the debate. Some references that deal with this topic include [8, 16].

- **Experts can join or leave the debate at any time**: as the debate of experts is taking place in an online environment, it is not unusual that a certain expert must leave the process before it is finished. Furthermore, additional experts can be invited to the process after it has begun. Therefore, it is an important task to design GDMs methods that can allow the set of experts to be modified at any time during the process. Some references that deal with this topic include [22, 28, 43].

- **Exploitation of the debate information**: Most of the GDM methods available in the literature do not make use of the information that experts share during their debate, but only focus on preferences provided by the experts. Whilein general preferences offer a reliable summary about experts' opinion, they do not contain all the information that has appeared in the debate. Therefore, it could be desirable to design methods that can record and take advantage of that information. When debating and carrying out decisions over the Internet, the transcriptions of the information that each expert has shared in the debate can be extracted and analyzed. This can help to comprehend what the experts aim to achieve and aid them in the decision process. Some references that deal with this topic include [15, 31, 33].

In this paper, a novel GDM method for dynamic contexts with a high number of alternatives is presented. As an important component of the model, the information contained in the debate texts is used in order to retrieve a reduced set of alternatives that the experts can use in further discussion and carry out the ranking process. In order to extract information from the debate transcriptions, sentiment analysis procedures [41, 53] are used. Since decisions are dynamic and desirable characteristics may vary, the set of alternatives is updated in each round of the decision process. In order to store all the information related to the alternatives in a comfortable and intuitive manner, fuzzy ontologies with type-2 and hesitant fuzzy sets are employed.

The presented methodology is novel and innovative due to the fact that it includes the following features:

- **Information is extracted directly from debate texts**: By using sentiment analysis, the information for reducing the initial set of alternatives is obtained directly from the transcriptions of the debate texts. This entails two different advantages. First, the number of interactions that experts make with the computational system is reduced making the process easier for them. Second, they can express themselves in a comfortable way using free text which is how they usually communicate.

- **Hesitant fuzzy ontology is used for storing alternatives related information**: In most of the cases, the information that is stored on the fuzzy ontology is quite imprecise. In this paper, a novel fuzzy ontology design which uses type-2 hesitant fuzzy sets is presented. They allow the fuzzy ontology to store the information in a more flexible way. For instance, several labels can be assigned when describing how an alternative fulfills a specific characteristic.

- **It is designed for working with a high number of alternatives:** Thanks to fuzzy ontologies, it is possible to carry out GDM processes that have a high number of alternatives. By performing queries, experts can focus on the most promising alternatives. Also, the information that is related with the alternatives, which can be also quite high, is correctly managed by the fuzzy ontology. Thanks to this, experts must only focus on deciding which are the better criteria leaving to the fuzzy ontology the task of deciding which alternatives fulfill it.

- **It works on dynamic contexts**: The designed GDM process allows experts and alternatives sets to be modified at any time. The information that the experts are analyzing and the availability or adequateness of including them in the process may change. Therefore, it is important to design GDM methods where the set of alternatives and experts may vary. If a designed GDM method is not capable of adapting itself to real world problems where the information is constantly being updated and where the decision setting can change, then it cannot be correctly employed.

The proposed methodology is tested using an example in which members of a political party have to decide on their final candidate for an upcoming election (cf. the Democratic Party in the USA and the Presidential election in 2020). In the example, 20 candidates are evaluated according to 10 criteria in order to compare and rank them. Criteria in this and similar situations is rather abstract and subjective since it contains elements such as charisma, ability to communicate a political message, etc. It is necessary to apply a method that is capable of dealing with imprecise and linguistic information. In practice, information about the candidates can be obtained from the continuous flow of material that is available on social media, newspapers and TV. Furthermore, candidates can join or leave the process at any time. Therefore, the used fuzzy ontology must be dynamically updated in order to reflect all the changes during the decision process.

This paper is organized as follows. In section 2, basic concepts needed to understand the presented GDM method are explained. In section 3, the proposed novel method is detailed. In section 4, an application example is shown. In section 5, advantages, drawbacks and related literature are discussed. Finally, some conclusions are pointed out.

2. Preliminaries

In this section, the basis needed to comprehend the proposed method are presented. We start with a general background on GDM methods in 2.1, followed by the basics of sentiment analysis in subsection 2.2 and fuzzy ontologies in subsection 2.3.

2.1. Group Decision Making

A GDM problem can be formally defined as follows [14]:

Definition 2.1. Let us consider a set of experts $E = \{e_1, \dots, e_n\}$ and a set of alternatives, $X = \{x_1, \dots, x_m\}$. A GDM method consists of defining the process in which the set of experts ranks the set of alternatives by providing a set of preferences, P^k, that are used by the system to calculate the final ranking of alternatives.

In practice, P^k is typically represented as a preference relation matrix with p_{ij}^k indicating how much e_k prefers x_i over x_j. Furthermore, as we typically consider dynamic contexts, the set of experts and alternatives can vary during the whole process. Therefore, the notation E_i and X_i is used where i indicates the ith round of the GDM process.

Generally, in order to solve a GDM problem, the following steps need to be performed (as depicted in Figure 1):

- **Providing preferences**: After a debate of experts sharing and discussing their ideas, each one provides his/her preferences.
- **Calculating the collective preference matrix**: The provided preferences are aggregated into a collective preference matrix indicating the overall opinion of all the experts.
- **Calculating consensus measures**: in GDM problems, the process normally continues until experts reach an agreement/consensus. It is of great importance to measure the level of consensus [2, 3, 10] and encourage the experts to debate until they reach an acceptable level or a pre-specified number of rounds is reached.

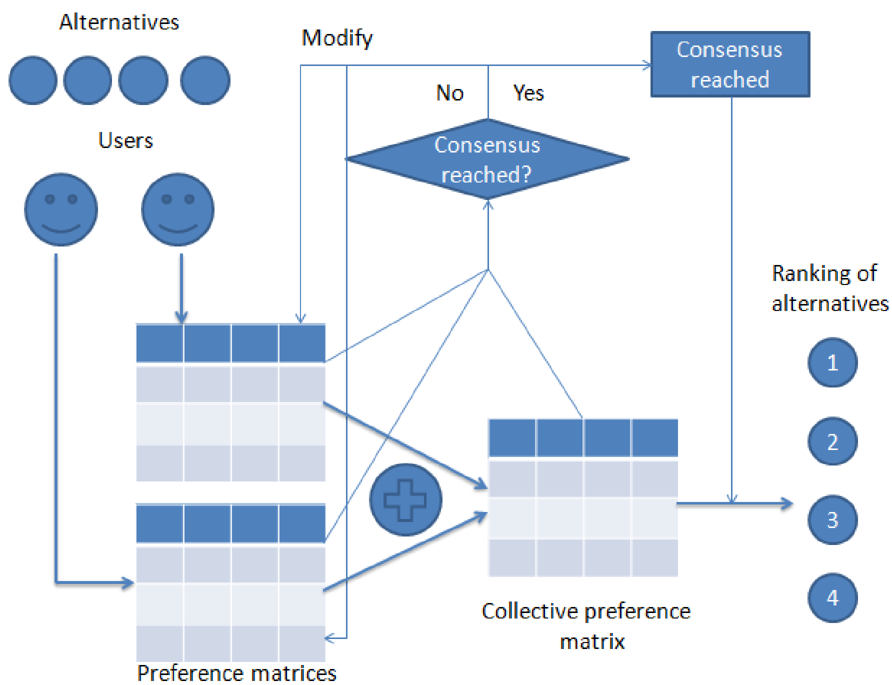

Figure 1: Group Decision Making scheme

- **Calculating final ranking results**: Using the collective preference matrix, selection measures and operators [20, 46] can be used to obtain the final ranking of the alternatives.

GDM methods has gained significant attention in the last decades, with new proposals appearing in the literature continuously. Focusing on recent years, in [31], sentiment analysis is used in order to analyze the GDM processes carried out on the Web. In [26], a comparative study on consensus measures is carried out. In [23], intuitionistic 2-tuple linguistic label sets are used for dealing with multi-attribute GDM environments. In [39], authors present a novel representation for intuitionistic fuzzy systems that they apply on Critical Decision Making. In [7], GDM environments where experts' influence is used to generate recommendations are introduced. In [50], trust propagation among the experts is used in order to develop a visual consensus model for GDM methods that are carried out on social networks. In [5], a method that estimate missing preferences using social influence among the experts is presented. In [6], fuzzy rankings are used in order to rank alternatives in GDM environments. In [24], a three-way decision approach that

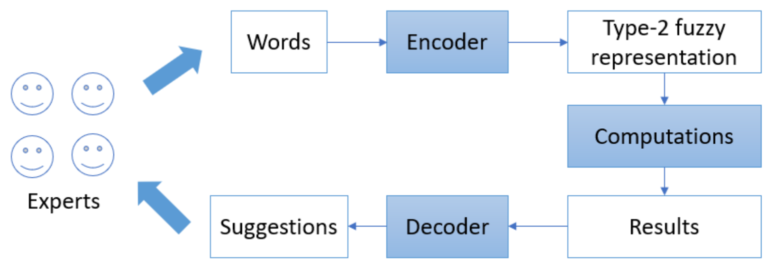

Figure 2: Perceptual computing scheme.

uses intuitionistic fuzzy sets is used to solve multi-attribute decision making problems. In [21], a linguistic scale function that transforms the semantics corresponding to hesitant linguistic terms into the linguistic preference values is proposed. The presented methodology is applied on fire rescue plans. In [12], fuzzy probabilistic rough sets and probability theories are uses in order to assist decision makers in the analysis of intelligent information coming from terrorist groups. Finally, in [51], a consensus model using hesitant fuzzy information and changeable clusters is proposed to deal with situations involving a large number of experts.

2.2. Perceptual Computing scheme using sentiment analysis procedures

Computers and humans use different means for expressing themselves. While computers were built to deal with numerical and exact information, humans tend to express themselves using imprecise and conceptual information. In order to reduce this gap, there is a need for methods that are capable of allowing a computer to extract information from natural language data.

Sentiment analysis procedures [4, 41] try to elucidate the sentiment of the user as expressed in a piece if text. By analyzing the type of words and expressions that a user employs, it is possible to comprehend how he/she feels about the topic that is discussed. Based on this, a system can provide assistance to experts in a luminous way. This data processing approach is called perceptual computing as depicted in Figure 2. Recent contributions focusing on perceptual computing [13, 25, 38].

There are several approaches in the literature to be used for sentiment analysis, including the bag of words approach [47], utilized in this article. A typical bag of words approach includes the following steps as shown in Figure

3:

- **Selecting target sentiments**: A set of sentiments to be detected in the text need to be specified. The analysis can be performed on different levels: (i) focusing on the detection of specific sentiments such as anger, or (ii) determining on a general level whether the user's attitude is positive or negative.

- **Obtaining list of words related to sentiments**: Keeping the goal of the analysis in mind, a list of characterizing words is identified for each sentiment. The words are selected in a way to provide an appropriate representation of experiencing the specific emotion.

- **Analyzing the target texts**: Based on searching the texts for the words generated in the previous step, the number of hits for each sentiment is stored. If the number of hits is above a certain threshold, the writer of the text is considered to express the sentiment when creating the text.

- **Showing final results**: After carrying out the analysis, each of the analyzed texts have zero, one or several sentiments attached.

Sentiment analysis methods are increasingly presented in the literature as applied to problems related to GDM. For instance, in [33], sentiment analysis procedures are used in order to carry out GDM processes directly over the debate texts of the experts. In [11], an ontology for sentiment analysis is built. In [17], a comparison on sentiment analysis approaches is performed and applied to the tourism domain. In [1], successes on developing a hybrid sentiment analysis and future challenges are depicted. Finally, in [44], sentiment analysis is used to detect conflicts in legislative speeches.

2.3. Fuzzy Ontologies

Fuzzy ontologies [49] are an extension of standard ontologies that can be used for representing imprecise information. For this purpose, the fuzzy sets theory is employed. Thanks to fuzzy ontologies, it is possible to represent information in an organized way. Also, it provides us with means that allow us to retrieve information that fulfill a certain set of characteristics. Formally, a fuzzy ontology can be defined as a tuple $< I, C, R, F, A >$ (a graphical representation presented in Figure 4), where:

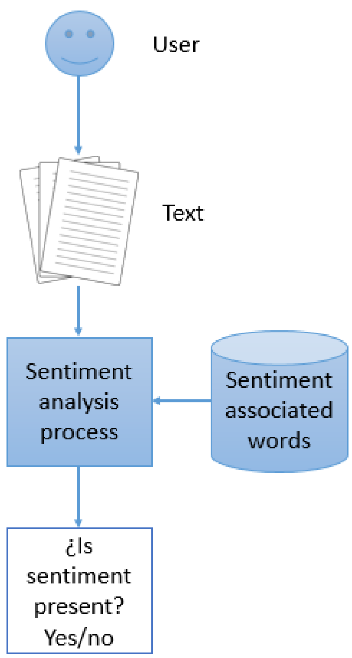

Figure 3: Sentiment analysis scheme.

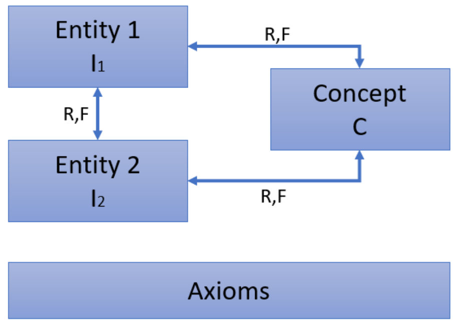

Figure 4: Fuzzy ontology scheme.

- I is the set of entities;
- C is the set of concepts used to describe the set of entities;
- R is the set of crisp relations indicating whether an entity fulfills a concept or not;
- F is the fuzzy relation indicating that an entity fulfills a concept at a certain degree. In this paper we will use hesitant fuzzy linguistic term sets where each label has an associated interval type-2 fuzzy set for this purpose.
- A is the set of axioms describing rules that the elements of the fuzzy ontology must fulfill.

In order to represent the information, each entity is associated to a set of concepts that are applicable to them. Entities are elements that are described in the ontology while concepts are the characteristics associated to them. If a fuzzy ontology relation is used, a value in the interval [0,1] indicating the fulfillment degree is assigned to each entity and concept pair.

Fuzzy ontologies are frequently employed in recent literature. For instance, in [30], an automatic procedure to generate fuzzy ontologies based on Internet opinions is presented. In [45], a review on type-2 fuzzy ontologies is carried out. In [52], a process to store fuzzy ontologies in fuzzy relational databases is shown. Finally, in [19], a formal approach for building fuzzy XML data models based on OWL 2 ontologies is presented.

3. A novel dynamic Group Decision Making with Fuzzy Ontology Support

In this paper, a novel dynamic GDM method with Fuzzy Ontology support for providing a reasonable set of alternatives for the experts to discuss about is presented. In order to carry out this process, the following steps are performed as depicted in Figure 5:

1. **Defining the fuzzy ontology**: A Fuzzy Ontology representation of information about the alternatives to be discussed has to be created.
2. **Extracting information from the debate**: Experts carry out a debate to elucidate which are the desirable characteristics of the alternatives. Debate transcriptions are analyzed using sentiment analysis in order to extract information about the alternatives' requirements.
3. **Generating a reduced set of alternatives**: Using the requirements extracted in the previous step and by performing fuzzy queries, a reduced set of alternatives that better fit the requirements are selected.
4. **Performing GDM computations**: After the experts formulate their preferences, ranking results and consensus measures are calculated for the reduced set of alternatives. If another GDM round is required, the process is repeated from point 2.

3.1. Defining the interval type-2 hesitant fuzzy ontology

As the first step, a fuzzy ontology about the alternatives is constructed. This can be done manually or by defining a conversion process from an existing database. The required fuzzy ontology can be built in the following steps:

- **Defining the entities**: Each alternative is considered as an entity.
- **Defining the concepts**: Each concept is a description about an specific feature of the alternatives. Characteristics that the experts perceive as relevant about the alternatives should be included here.
- **Defining the entity-concept relations**: Relations between entities and concepts represent the way that alternatives fulfill the associated characteristics. In order to promote flexible descriptions based on conceptualization, linguistic label sets can be used. Specifically, each alternative-concept relation is defined as a hesitant linguistic term, i.e.

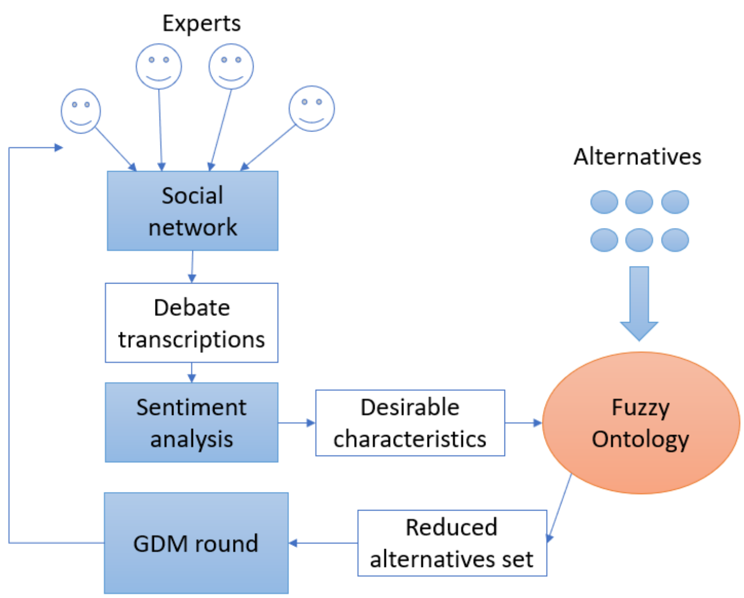

Figure 5: Presented method scheme.

several labels can be attached for each alternative and concept pair. Furthermore, in order to provide flexibility on the labels' definition, interval type-2 fuzzy sets are used. Formally, the relation between alternative x_i and concept c_j, $R(x_i, c_j)$, can be defined using the linguistic label set $S = \{s_1, \ldots, s_g\}$ as follows:

$$R(x_i, c_j) = \{\{s_v, \ldots, s_w\}|v, \ldots, w \in 1, \ldots, g|v \neq w\} \tag{1}$$

Each label is defined as a interval type-2 fuzzy set. An interval type-2 fuzzy set can be formally defined as:

$$\tilde{A} = \{x, UMF(x), LMF(x)\}, \forall x \in X \tag{2}$$

where UMF is the upper membership function and LMF is the lower membership function.

For exemplary purposes, the linguistic label set $S^7 = \{s_1, \ldots, s_7\}$ presented in Table 1 using triangular form notation can used. Our choice of representation is motivated by the extra flexibility provided by type-2 fuzzy sets over standard fuzzy sets.

Label	UMF	LMF
s_1	(0,0,0.1)	(0,0,0.05)
s_2	(0,0.1,0.3)	(0.05,0.1,0.2)
s_3	(0.1,0.3,0.5)	(0.2,0.3,0.4)
s_4	(0.3,0.5,0.7)	(0.4,0.5,0.6)
s_5	(0.5,0.7,0.9)	(0.6,0.7,0.8)
s_6	(0.7,0.9,1)	(0.8,0.9,1)
s_7	(0.9,1,1)	(0.95,1,1)

Table 1: Fuzzy sets used for defining the labels in S.

Depending on the tackled problem, the fuzzy ontology may need to be updated with new information or some entities need to be removed. When this situation appears, the fuzzy ontology must be modified and the chosen alternatives for the discussion must be recalculated according to the new representation.

3.2. Extracting information from the debate of experts

The debate can be initiated once that the fuzzy ontology is constructed. Experts can use a social network or an online forum. In order to obtain the most desirable characteristics for the alternatives from the transcriptions of the debate, sentiment analysis procedures are employed. In this paper, the bag of words sentiment analysis approach depicted in subsection 2.2 will be used. In order to carry out this process, the next steps are followed:

- **Defining lists of positive and negative words**: In the sentiment analysis bag of word approach, several lists of sentiments' related words must be generated in order to track the desired postures. Since our method is tracking opinions, a list of positive and negative words will allow us to identify positive and negative feelings on the alternatives.

- **Classifying the texts according to the alternatives characteristics**: Each concept has an associated keyword list, kw_i that contains words that unambiguously identify the concept. Using this list, one can identify the concept that is mainly referred by each text by analysing the debate transcriptions. Based on this analysis, the system can create the indexed family T, defined as

$$T = \{t_{ij}\}|c_i \in C, e_j \in E \quad (3)$$

where t_{ij} is a set of texts provided by e_j that mention how the c_i should be fulfilled by the alternatives.

- **Searching for positive and negative words in the texts**: Once the classification is performed, words from the positive and negative lists can be searched for in order to determine the desirable characteristics. Thanks to this, it is possible to identify how the experts were feeling when writting each of the texts. For each expert and concept, values $pwcount_{ij}$ and $nwcount_{ij}$ are calculated. They indicate, respectively, the number of times that positive and negative words have been provided by the experts when the characteristic c_i was being mentioned by e_j. Positive words indicate that the expert values positively the characteristic since he/she has positive sentiments about it. On the other way around, negative words indicate that the expert does not like it.

- **Calculating the preference value for each expert and characteristic**: Once that the sentiment analysis procedure have been performed, it is possible to use the *pwcount* and *nwcount* values for calculating a numerical value, p_{ij}, that indicates the level of fulfillment that the alternatives should have about an specific concept:

$$p_{ij} = \frac{pwcount_{ij} - nwcount_{ij}}{pwcount_{ij} + nwcount_{ij}} \tag{4}$$

While this value is in the interval [-1,1], one can obtain a [0,1] representation by carrying out a domain conversion:

$$p'_{ij} = \frac{p_{ij} + 1}{2} \tag{5}$$

- **Obtaining the collective desirable value for c_i**: By aggregating the p_{ij} values for each expert, the desirable value, d_i, for the concept c_i can be calculated as

$$d_i = \sum_{j=1}^{n} w_j \cdot p_{ij} \tag{6}$$

where w is a weighting vector indicating the importance of each expert. In lack of information in a generic case, equal weights can be used for each expert. The d_i values indicate the level of fulfillment of concept c_i that alternatives should have. By using this value, a query over the fuzzy ontology can be specified in order to retrieve a reduced set of alternatives that are closer to the d_i values.

3.3. *Generating the reduced set of alternatives for the Group Decision Making round*

The query mentioned in the previous step does not have to include all the concept values. In case there are some concepts not mentioned in the debate or insufficient information is provided about them, they can be excluded from the query. In order to formulate the query, the following parameters must be established:

- **Importance given to each concept**: By using $pwcount_{ij}$ and $nwcount_{ij}$, it is possible to measure the importance given to each of the concepts during the debate. Termed as the degree of appearance and denoted as da_i, it can be calculated as

$$da_i = \sum_{j=0}^{n} (pwcount_{ij} + nwcount_{ij}) \tag{7}$$

  The higher the value of da_i is, the more importance the concept had during the debate. In order to compare different degrees of appearance, da_i can be normalized to the [0,1] interval as

$$dan_i = \frac{da_i}{\sum da_i} \tag{8}$$

- **Set of concepts**: The set of concepts that should be included in the query must be determined. For this purpose, one of the following approaches can be selected:
  - **Selecting the λ most mentioned concepts**: By using the da_i values, it is possible to sort the concepts according to the importance that they were given in the discussion and select the λ highest valued concepts for the query.
  - **Using the λ concepts that have an importance value higher than β**: It is possible to establish a threshold, β, based on the da_i values and select only those concepts whose associated value is higher.
- **Number of results, z**: The number of results establishes the number of alternatives that the experts will consider. A number between 3 and 7 is recommended so that the experts do not get lost among too many

possibilities and the debate can be carried out in a comfortable and efficient way.

- **Establishing the weights of selected concepts**: Expression (8) can be applied over the set of selected concepts in order to calculate the associated weights.

Once the set of weights, W, and set the of selected concepts, $C = \{c_1, \ldots, c_o\}$ have been calculated, it is possible to retrieve the set of α alternatives that fulfill the experts' requirements the most. For this purpose, a similarity value for each alternative according to the query, Q, is calculated as follows:

$$s(x_i, Q) = \phi(sim(d_i, R(x_i, c_j)))|\forall j \in [1, o] \tag{9}$$

where ϕ is the mean operator and $sim(d_i, R(x_i, c_j))$ can be calculated as follows:

$$sim(d_i, R(x_i, c_j)) = \phi(max(\mu_h(d_i, c_j))) \tag{10}$$

where $\mu_h(d_i, c_j)$ is the set of intervals that are obtained after calculating the membership value of d_i to all the interval type-2 fuzzy sets that are associated to the labels of the relation $R(x_i, c_j)$. Once that the similarity values $s(x_i, Q)$ have been calculated and sorted, a set with the α most appropriate alternatives can be generated.

3.4. Carrying out the dynamic Group Decision Making process

In order to rank the generated reduced set of alternatives, the scheme described in subsection 2.1 can be employed. The steps that must be followed are described in more detail below:

1. **Providing preferences**: Experts provide preferences using preference relation matrices. Value p_{ij}^k indicates how much e_k prefers x_i over x_j. In order to allow the experts to provide preferences in a comfortable way, the linguistic label set $S = \{s_1, \ldots, s_7\}$ can be used. Each expert may select the linguistic label set that he/she prefers if multi-granular fuzzy linguistic modelling procedures [29, 35] are used.
2. **Calculating the collective preference matrix**: Preferences provided by the experts can be aggregated to obtain a collective preference matrix. Intervals defining the fuzzy sets of the labels provided are aggregated in order to generate a collective preference matrix where an

interval is assigned to each pair of alternatives. The intervals are generated by calculating the mean between UMF and LMF membership values for each label. For this purpose, the following expression can be used:

$$c_{ij} = \sum_{k=1}^{n} \phi(p_{ij}^{k}) \tag{11}$$

where ϕ represents the mean operator over the labels associated intervals.

3. **Calculating consensus measures [26]**: Measuring consensus will allow us to determine whether another GDM round should be carried out or an agreement is reached. First, similarity between each expert, e_k, and the collective group is calculated as

$$sm_{ij}^{k} = sim(p_{ij}^{k}, c_{ij}) \tag{12}$$

where sim refers to a similarity function. For exemplary purposes, the 1-norm distance can be used. The consensus matrix is calculated by aggregating all the obtained sm_{ij}^{k} values as follows:

$$\forall i, j \in [1, m]; cm_{ij} = \phi(sm_{ij}^{1}, \ldots sm_{ij}^{n}) \tag{13}$$

By using cm, it is possible to measure consensus at three different levels:

- **Pair of alternatives level**: Measures the agreement that experts have when comparing two different alternatives. It can be calculated as follows:

$$cp_{ij} = cm_{ij} \tag{14}$$

- **Alternatives level**: Measures the agreement that experts have on a specific alternative. It is calculated as stated below:

$$ca_i = \phi(cp_{ij}, cp_{ji}; j = 1 \ldots m \wedge j \neq i) \tag{15}$$

- **Global consensus level**: By aggregating all the ca_i values, it is possible to obtain an overall consensus value for the GDM round:

$$cr = \phi(ca_i; i = 1 \ldots m) \tag{16}$$

4. **Calculating the ranking of alternatives**: In order to calculate the rankings, the mean between guided dominance and guided non dominance degree operators, GDD and GNDD respectively, can be used. GDD and GNDD operator expressions are defined as:

$$GDD_i = \phi(c_{i1}, c_{i2}, \ldots, c_{i(i-1)}, c_{i(i+1)}, \ldots, c_{in}) \quad (17)$$

$$GNDD_i = \phi(c^s_{1i}, c^s_{2i}, \ldots, c^s_{(i-1)i}, c^s_{(i+1)i}, \ldots, c^s_{ni}) \quad (18)$$

   where

$$c^s_{ji} = \max\{c_{ji} - c_{ij}, 1\}$$

   The final ranking of alternatives can be calculated as the mean of the calculated values:

$$RV_i = (GDD_i + GNDD_i)/2, \forall i \in [0, m] \quad (19)$$

   It is important to note that in our model, these operators are applied over intervals. In order to rank the alternatives according to the obtained RV_i values, the intervals' centroids can be used.

5. **Modifying the set of experts**: At any time of the process, any expert can join or leave. When an expert abandons the process, his/her preferences are deleted from the system and the ranking needs to be recalculated using only the texts of the remaining experts. Therefore, the actual GDM round stops and the GDM process goes back to the *generating the reduced set of alternatives* step depicted in subsection 3.3. The reduced ranking of alternatives is recalculated and the process continues from there. New experts can also join the debate at any time of the process. In this case, the actual GDM round stops and it goes back to the *extracting information from the debate of experts* step depicted in subsection 3.2. The debate on the characteristics is restarted and the new experts share their opinion with the ones that were there before. The process continues from there as usual.

4. Illustrative Example

In this section an example application of the proposed method is presented. In the example, we assume that a political party needs to decide which candidate should be nominated for an upcoming election. At the start

Concept	**Description**	x_1	x_2	x_3
c_1	Charisma	$\{s_1, s_2\}$	$\{s_6, s_7\}$	$\{s_4, s_5\}$
c_2	Communication	$\{s_5, s_6, s_7\}$	$\{s_1, s_2\}$	$\{s_5, s_6\}$
c_3	Honesty	$\{s_4, s_5, s_6\}$	$\{s_6, s_7\}$	$\{s_3, s_4\}$
c_4	Scandal resistance	$\{s_6, s_7\}$	$\{s_1, s_2\}$	$\{s_3, s_4\}$
c_5	Intelligence	$\{s_2, s_3\}$	$\{s_1, s_2\}$	$\{s_2, s_3\}$
c_6	Diplomacy	$\{s_1, s_2\}$	$\{s_6, s_7\}$	$\{s_2, s_3\}$
c_7	Passion	$\{s_4, s_5\}$	$\{s_5, s_6\}$	$\{s_2, s_3\}$
c_8	Humor	$\{s_2, s_3\}$	$\{s_6, s_7\}$	$\{s_5, s_6\}$
c_9	Thoughtfulness	$\{s_5, s_6\}$	$\{s_6, s_7\}$	$\{s_4, s_5\}$
c_{10}	Bravery	$\{s_5, s_6\}$	$\{s_4, s_5\}$	$\{s_3, s_4\}$

Table 2: Descriptions of the fuzzy ontology concepts along with some relation examples.

of the process, there are 25 candidates $X = \{x_1, \ldots, x_{25}\}$ that should be evaluated and ranked by a set of 4 experts, $E = \{e_1, e_2, e_3, e_4\}$. Information about 10 different characteristics of the candidates, $C = \{c_1, \ldots, c_{10}\}$, is available. In Table 2, descriptions of the concepts along with relation values that they have for alternatives x_1, x_2 and x_3 are shown. In this example, consensus threshold is set to 0.75. When the global consensus value becomes higher, it implies that the experts have reached an agreement and the GDM process can end.

Experts carry out a debate in which they discuss about the desirable characteristics. The transcriptions of the debate texts are sorted according to the characteristic that they refer. Next, the number of positive and negative words that experts use is calculated. The four most used characteristics will be employed in order to retrieve the reduced set of alternatives. After counting the number of word matches, this set is compound by $\{c_2, c_4, c_7, c_8\}$. The number of positive and negative words provided by the experts about those concepts is shown in Table 3. By using expressions (4) and (6), it is possible to calculate the most desirable value for each of the concepts. Results are shown in Table 4. For instance, for e_2 and c_2, p value is computed as follows:

$$p_{21} = \frac{7-1}{8} = 0.75$$

Experts	c_2		c_4		c_7		c_8	
	+	-	+	-	+	-	+	-
e_1	7	0	6	1	0	4	5	1
e_2	7	1	7	2	1	5	7	1
e_2	4	3	8	2	0	4	8	1
e_4	6	1	10	1	2	1	10	2

Table 3: Number of positive and negative words provided by the experts for the most discussed characteristics.

Experts	c_2	c_4	c_7	c_8
e_1	1	0.8571	0	0.833
e_2	0.875	0.7777	0.1666	0.875
e_2	0.5714	0.8	0	0.888
e_4	0.8571	0.909	0.6666	0.833
d_i	0.8258	0.836	0.2083	0.857

Table 4: Calculation of the desirable values.

In order to normalize the value, expression (5) is used as follows:

$$p'_{21} = \frac{0.75 + 1}{2} = 0.875$$

In these calculations we consider all the experts having the same impact on the process.

By using the number of times that concepts were mentioned in the debate, expression (8) can be used in order to determine the weight that each concept must have on the query. The obtained concept weighting vector is calculated as

$$W = \{0.2457, 0.3135, 0.1441, 0.2966\}$$

Once the d_i values and their associated weighting vector is calculated, similarity values between each of the alternatives and the query can be calculated. Results for the eight closest alternatives are shown in Table 5.

After analyzing the query results, experts decide to carry out the GDM process using the three most valued candidates. Therefore, $\{x_{25}, x_{21}, x_3\}$ are the chosen alternatives. First, the experts provide their preferences using a

Alternative	Similarity value
x_{25}	0.5196
x_{21}	0.4104
x_3	0.3565
x_{13}	0.3172
x_{10}	0.3115
x_5	0.2929
x_1	0.2722
x_{23}	0.2525

Table 5: Similarity values result.

matrix:

$$P^1 = \begin{pmatrix} - & s_7 & s_6 \\ s_3 & - & s_2 \\ s_1 & s_1 & - \end{pmatrix} P^2 = \begin{pmatrix} - & s_6 & s_7 \\ s_3 & - & s_3 \\ s_1 & s_2 & - \end{pmatrix}$$
$$P^3 = \begin{pmatrix} - & s_7 & s_7 \\ s_4 & - & s_3 \\ s_2 & s_1 & - \end{pmatrix} P^4 = \begin{pmatrix} - & s_6 & s_6 \\ s_2 & - & s_1 \\ s_1 & s_1 & - \end{pmatrix}$$

By calculating the interval from the aggregation of UMF and LMF membership values, the following results are obtained:

$$P^1 = \begin{pmatrix} - & [0.925, 1] & [0.75, 1] \\ [0.15, 0.45] & - & [0.025, 0.25] \\ [0, 0.075] & [0, 0.075] & - \end{pmatrix}$$
$$P^2 = \begin{pmatrix} - & [0.75, 1] & [0.925, 1] \\ [0.15, 0.45] & - & [0.15, 0.45] \\ [0, 0.075] & [0.025, 0.25] & - \end{pmatrix}$$
$$P^3 = \begin{pmatrix} - & [0.925, 1] & [0.925, 1] \\ [0.35, 0.65] & - & [0.15, 0.45] \\ [0.025, 0.25] & [0, 0.075] & - \end{pmatrix}$$
$$P^4 = \begin{pmatrix} - & [0.75, 1] & [0.75, 1] \\ [0.025, 0.25] & - & [0, 0.075] \\ [0, 0.075] & [0, 0.075] & - \end{pmatrix}$$

After aggregating all the matrices, the following collective preference matrix

	x_{25}	x_{21}	x_3
GDD	[0.725,0.8333]	[0.25,0.41]	[0.1708,0.2458]
GNDD	1	[0.777,0.816]	[0.6437,0.6979]
Ranking	[0.8625,0.9166]	[0.5135,0.6177]	[0.4343,0.4447]

Table 6: Ranking results for the alternatives.

is obtained:

$$C = \begin{pmatrix} - & [0.8375, 1] & [0.8375, 1] \\ [0.16875, 0.45] & - & [0.08125, 0.30] \\ [0.00625, 0.11875] & [0.00625, 0.11875] & - \end{pmatrix}$$

Once the collective matrix has been calculated, it is possible to obtain the ranking of alternatives by applying GDD and GNDD operators as shown in Table 6. It can be seen that the ranking is $\{x_{25}, x_{21}, x_3\}$, x_{25} being the most voted alternative.

Finally, consensus results are calculated in order to determine whether experts have reached a sufficient agreement level. First of all, CM matrix is calculated by using (13). This matrix shows the consensus reached for each pair of alternatives. It should be taken into account that the presented values are expressed in the interval [0,1] with 1 indicating total consensus. The result of this calculation is the following:

$$CM = \begin{pmatrix} - & [0.9125, 1] & [0.7437, 1] \\ [0.9, 0.9093] & - & [0.8562, 0.9312] \\ [0.9343, 0.9906] & [0.9125, 0.9906] & - \end{pmatrix}$$

Afterwards, expression (15) is applied in order to calculate the consensus for each alternative:

$$CA = \{[0.9171, 0.95], [0.9515, 0.9562], [0.8375, 0.9281]\}$$

Finally, values from vector ca can be aggregated in order to calculate the global consensus for the decision round as the interval [0.913,0.933]. Since the (centroid of the) obtained consensus interval is above the established threshold, 0.75, then there is no need for carrying out any more GDM rounds.

In case another GDM round was needed, experts would carry out another debate. From that debate, a new set of desirable characteristics for the alternatives could be obtained. A new reduced set of alternatives would be generated by using the information provided. Finally, the exposed GDM process could be repeated using the new set of alternatives. The more that the experts communicate among themselves, the more points of views are shared making the extracted information more accurate and supported by the whole set of experts. This would result in a more reliable reduced set of alternatives for the experts to rank.

Considering another possible situation, we can assume that while the experts are debating, candidate x_3 leaves the election and another two candidates, x_{26} and x_{27}, join the process. If this happen, there is a need to stop the process and recalculate the candidates ranking. In this new environment, the five most voted candidates could be $\{x_{25}, x_{21}, x_{13}, x_{10}, x_5\}$. Therefore, candidate x_3 is replaced by x_{13} in the discussion and the GDM debate is restarted.

5. Discussion

In this paper, a novel dynamic GDM method for dealing with environments with a high number of alternatives is presented. A perceptual computing scheme is used in order to extract information directly from the debate. Sentiment analysis is employed in order to extract the desirable characteristics of the alternatives. Finally, a fuzzy ontology is used in order to store the information from the alternatives and obtain the reduced set of alternatives that the experts will rank. The proposed method presents the following advantages:

- **Information is extracted directly from the debate**: Most of the available methods in literature use preferences directly provided by the experts. Although it is a good approach, debate transcription contains more information about what the experts really think. Therefore, by using debate transcriptions, less information is wasted. Our method presents a novel method that uses a perceptual computing approach that employs sentiment analysis in order to extract information directly from the debate. Consequently, a reduced set of alternatives is generated using all the valuable information shared by the experts.

- **A novel relation type in the Fuzzy Ontology**: The information that is available on the Internet and that the experts provide in the debate is imprecise and expressed using free text. In this paper, a novel type of fuzzy relation is presented. Thanks to the presented hesitant type-2 fuzzy scheme, it is possible to assign several labels to each entity-concept relation. This way, the representation capability of the fuzzy ontology is boosted. Thanks to type-2 fuzzy sets, the inner representation of each label is also more flexible compared to normal fuzzy sets.

- **Experts and alternatives can vary during the process**: Recent GDM methods are carried out over the Web. This new communication mean promotes a flexible scheme where experts and alternatives can appear or be removed at any time. The presented method takes this into account and allows experts to be added and removed. In each step, a new set of alternatives is selected by taking into account the debate information carried out in the GDM round.

- **The process can generate a reduced set of alternatives**: Human mind can only deal with a small amount of information at the same time. Therefore, we need methods that can adapt information in a way that the experts can carry out a comfortable discussion. Using fuzzy ontologies and sentiment analysis, it is possible to extract information from the debate and carry out a query in order to determine the most desirable alternatives. By using this information, a reduced set of alternatives is generated. This process prevents experts from having to deal with large amounts of information. Since all the alternatives are ranked according to their similarity with the information extracted from the debate, it is possible to choose any number of alternatives to be included in the debate.

The method's main drawback relates to generating the fuzzy ontology. Although a large amount of information is available on Internet about almost any topic, there is a need to define a transformation process that converts that information into the required fuzzy ontology representation. Some guidelines about how to define this process can be found in [34].

In recent literature, some related methods can be found. Fuzzy ontologies have been used as a support system in some articles [8, 37, 42]. Although these articles use fuzzy ontologies in order to generate recommendations, they do not take into account a generic environment where experts can join or leave any time. Furthermore, these contributions focus on solving a specific problem, such as wine selection. Additionally, all these articles use fuzzy ontologies where each concept represents a specific label of a linguistic label set. This makes the fuzzy ontologies difficult to read, define and interpret and they have less representation flexibility than the novel model that is presented in this article. The presented fuzzy hesitant type-2 fuzzy relation makes the entities-concepts relations quite intuitive and easy to read and interpret to human beings as labels are directly assigned to the relations. Another important issue that distinguishes this article from previous research is that the set of alternatives can be updated in each round. This way, the set of alternatives is adapted to the changes of mind that can appear in the GDM debate.

One can also identify research in the literature that deals with the problem of large amount of alternatives without using fuzzy ontologies. For instance, in [36], card sorting techniques are used in order to allow the experts to create groups of alternatives to discuss about. The main drawback of this method is that it forces the experts to manage all the alternatives. In our method, experts only need to discuss about the alternatives characteristics. Consequently, they do not need to directly deal with every available alternative.

As it can be seen, the number of papers dealing with GDM methods with a large number of alternatives is not broad. Recent research on the topic [40, 54] is more focused on dealing with a high number of experts leaving criteria and alternatives set as reduced as in traditional GDM literature. Nevertheless, due to the large amount of information that is now available on the Internet, the development of methods that are capable of dealing with and help experts to process and discuss high number of alternatives are needed.

There is also research on dynamic GDM methods [22, 32] that allows the set of experts and alternatives to be modified at any time. Nevertheless, these methods focus on dealing with dynamic environments and do not consider the problems associated with large amount of information.

Although in [32], the described method works with high number of alternatives and experts, it does not consider any information related to the alternatives. Therefore, experts must find this information and get an idea about how to rank them on their own. In our new method, fuzzy ontologies help the experts to carry out an organized debate by managing all the alternatives related information. It is important to include tools that allow experts to manage all the alternative related information because, specially in environments where there is a high number of alternatives, experts can get lost among all the available data. This can lead to poor decision results due to the incapability of the experts to process all the information on their own.

It is also important to notice that there is little research on the application of sentiment analysis over GDM methods that employ tools to manage high amounts of information. Thanks to sentiment analysis, there is no need of an extra step where the experts have to explicitly provide the desirable characteristics of the alternatives to the system. This information is directly obtained from the debate. Also, this feature allows experts to share information in common language making the process much more comfortable for them. It should be noticed that improving human-computer communication and reducing the number of actions that experts must perform is critical in order to design GDM methods that correctly works in complex environments where participants may get lost due to the high amount of information that they have to deal with. Neither of the previous methods include this feature.

6. Conclusions

In this paper, a novel method to carry out dynamic GDM processes with a high number of alternatives has been presented. Since discussing all the alternatives at the same time is not possible for the experts, fuzzy ontologies are employed in order to assist them in the selection of a reduced set of alternatives to discuss about. In the presented method, experts do not have to directly provide their preferences to the fuzzy ontologies. Instead, sentiment analysis procedures are used in order to analyze the experts' debates and extract the most desirable set of alternatives. This way, the amount of information that experts need to provide to the system is small. Since all the debate transcriptions are analyzed, the system has access to all the information provided during the debate.

In order to increase the imprecision representation capability of the fuzzy ontology, relations between entities and concepts were designed as hesitant fuzzy linguistic term sets and labels are defined using interval type-2 fuzzy sets. Thanks to this, more than one label can be assigned to each relation. This improves the original fuzzy ontology representation capability.

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A dynamic group decision making process for high number of alternatives using hesitant Fuzzy Ontologies and sentiment analysis

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Abstract

The high spread of Internet and social networks have completely changed the way that Group Decision Making methods are designed, developed and implemented. Experts now operate in environments where a large amount of information is available and new ideas and participants can appear at any time; this results in a dynamically changing decision environment. In this paper, a novel group decision making method for dynamic contexts with a high number of decision alternatives is presented. As the main component of the proposal, a perceptual computing scheme is used in order to extract information from the experts. In the process, sentiment analysis is used when analysing the debate texts in order to obtain information for selecting the best alternatives on each round. Moreover, interval type-2 hesitant Fuzzy Ontologies are used in order to store the information related to alternatives. By combining interval type-2 and hesitant fuzzy sets, imprecise information can be represented in a comfortable and intuitive way within the ontology.

Keywords: Group Decision Making, Fuzzy Ontologies, Sentiment analysis, Computing with words, Type-2 hesitant fuzzy sets

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1. Introduction

Group Decision Making (GDM) as a field has gained significant and continuously increasing attention since its first appearance in the early 80's [9] until recently [18, 33, 36]. The recent growth in Internet usage, generated information and the appearance of social networks [48] have provoked a change in the way that GDM processes are designed and implemented. This new environment generates several challenges that are not handled appropriately by existing models. Some of the important challenges that motivated the proposal presented in this article include the following:

- **Large number of alternatives**: with the information explosion in the present digital age, the increased amount of generated insight result in an increased number of recognized decision alternatives. When facing a large number of alternatives, experts in a group can have more difficulties when trying to reach an agreement. Therefore, there is a need of developing tools that aid the experts to deal with this overload of alternatives. Some references that deal with this topic include [27, 36, 42].

- **Large amount of information about each alternative**: in theory, the more information an expert acquires on an alternative, the more informed the resulting decision should be as weak and strong points of individual alternatives can be easily recognized. However, beyond a limit, the amount of information related to the alternatives that the experts have to deal with would be quite difficult to manage. In order to solve this issue, it would be desirable to employ a tool capable of storing and organizing the information in an optimized way. One possible option is the use of fuzzy ontologies for this purpose [49]. Fuzzy Ontologies can provide the experts with a reduced set of alternatives that they can discuss about and information about the desirable characteristics of the alternatives can be directly extracted from the debate. Some references that deal with this topic include [8, 16].

- **Experts can join or leave the debate at any time**: as the debate of experts is taking place in an online environment, it is not unusual that a certain expert must leave the process before it is finished. Furthermore, additional experts can be invited to the process after it has begun. Therefore, it is an important task to design GDMs methods that can allow the set of experts to be modified at any time during the process. Some references that deal with this topic include [22, 28, 43].

- **Exploitation of the debate information**: Most of the GDM methods available in the literature do not make use of the information that experts share during their debate, but only focus on preferences provided by the experts. Whilein general preferences offer a reliable summary about experts' opinion, they do not contain all the information that has appeared in the debate. Therefore, it could be desirable to design methods that can record and take advantage of that information. When debating and carrying out decisions over the Internet, the transcriptions of the information that each expert has shared in the debate can be extracted and analyzed. This can help to comprehend what the experts aim to achieve and aid them in the decision process. Some references that deal with this topic include [15, 31, 33].

In this paper, a novel GDM method for dynamic contexts with a high number of alternatives is presented. As an important component of the model, the information contained in the debate texts is used in order to retrieve a reduced set of alternatives that the experts can use in further discussion and carry out the ranking process. In order to extract information from the debate transcriptions, sentiment analysis procedures [41, 53] are used. Since decisions are dynamic and desirable characteristics may vary, the set of alternatives is updated in each round of the decision process. In order to store all the information related to the alternatives in a comfortable and intuitive manner, fuzzy ontologies with type-2 and hesitant fuzzy sets are employed.

The presented methodology is novel and innovative due to the fact that it includes the following features:

- **Information is extracted directly from debate texts**: By using sentiment analysis, the information for reducing the initial set of alternatives is obtained directly from the transcriptions of the debate texts. This entails two different advantages. First, the number of interactions that experts make with the computational system is reduced making the process easier for them. Second, they can express themselves in a comfortable way using free text which is how they usually communicate.

- **Hesitant fuzzy ontology is used for storing alternatives related information**: In most of the cases, the information that is stored on the fuzzy ontology is quite imprecise. In this paper, a novel fuzzy ontology design which uses type-2 hesitant fuzzy sets is presented. They allow the fuzzy ontology to store the information in a more flexible way. For instance, several labels can be assigned when describing how an alternative fulfills a specific characteristic.

- **It is designed for working with a high number of alternatives:** Thanks to fuzzy ontologies, it is possible to carry out GDM processes that have a high number of alternatives. By performing queries, experts can focus on the most promising alternatives. Also, the information that is related with the alternatives, which can be also quite high, is correctly managed by the fuzzy ontology. Thanks to this, experts must only focus on deciding which are the better criteria leaving to the fuzzy ontology the task of deciding which alternatives fulfill it.

- **It works on dynamic contexts**: The designed GDM process allows experts and alternatives sets to be modified at any time. The information that the experts are analyzing and the availability or adequateness of including them in the process may change. Therefore, it is important to design GDM methods where the set of alternatives and experts may vary. If a designed GDM method is not capable of adapting itself to real world problems where the information is constantly being updated and where the decision setting can change, then it cannot be correctly employed.

The proposed methodology is tested using an example in which members of a political party have to decide on their final candidate for an upcoming election (cf. the Democratic Party in the USA and the Presidential election in 2020). In the example, 20 candidates are evaluated according to 10 criteria in order to compare and rank them. Criteria in this and similar situations is rather abstract and subjective since it contains elements such as charisma, ability to communicate a political message, etc. It is necessary to apply a method that is capable of dealing with imprecise and linguistic information. In practice, information about the candidates can be obtained from the continuous flow of material that is available on social media, newspapers and TV. Furthermore, candidates can join or leave the process at any time. Therefore, the used fuzzy ontology must be dynamically updated in order to reflect all the changes during the decision process.

This paper is organized as follows. In section 2, basic concepts needed to understand the presented GDM method are explained. In section 3, the proposed novel method is detailed. In section 4, an application example is shown. In section 5, advantages, drawbacks and related literature are discussed. Finally, some conclusions are pointed out.

2. Preliminaries

In this section, the basis needed to comprehend the proposed method are presented. We start with a general background on GDM methods in 2.1, followed by the basics of sentiment analysis in subsection 2.2 and fuzzy ontologies in subsection 2.3.

2.1. Group Decision Making

A GDM problem can be formally defined as follows [14]:

Definition 2.1. Let us consider a set of experts $E = \{e_1, \ldots, e_n\}$ and a set of alternatives, $X = \{x_1, \ldots, x_m\}$. A GDM method consists of defining the process in which the set of experts ranks the set of alternatives by providing a set of preferences, P^k, that are used by the system to calculate the final ranking of alternatives.

In practice, P^k is typically represented as a preference relation matrix with p^k_{ij} indicating how much e_k prefers x_i over x_j. Furthermore, as we typically consider dynamic contexts, the set of experts and alternatives can vary during the whole process. Therefore, the notation E_i and X_i is used where i indicates the ith round of the GDM process.

Generally, in order to solve a GDM problem, the following steps need to be performed (as depicted in Figure 1):

- **Providing preferences**: After a debate of experts sharing and discussing their ideas, each one provides his/her preferences.
- **Calculating the collective preference matrix**: The provided preferences are aggregated into a collective preference matrix indicating the overall opinion of all the experts.
- **Calculating consensus measures**: in GDM problems, the process normally continues until experts reach an agreement/consensus. It is of great importance to measure the level of consensus [2, 3, 10] and encourage the experts to debate until they reach an acceptable level or a pre-specified number of rounds is reached.

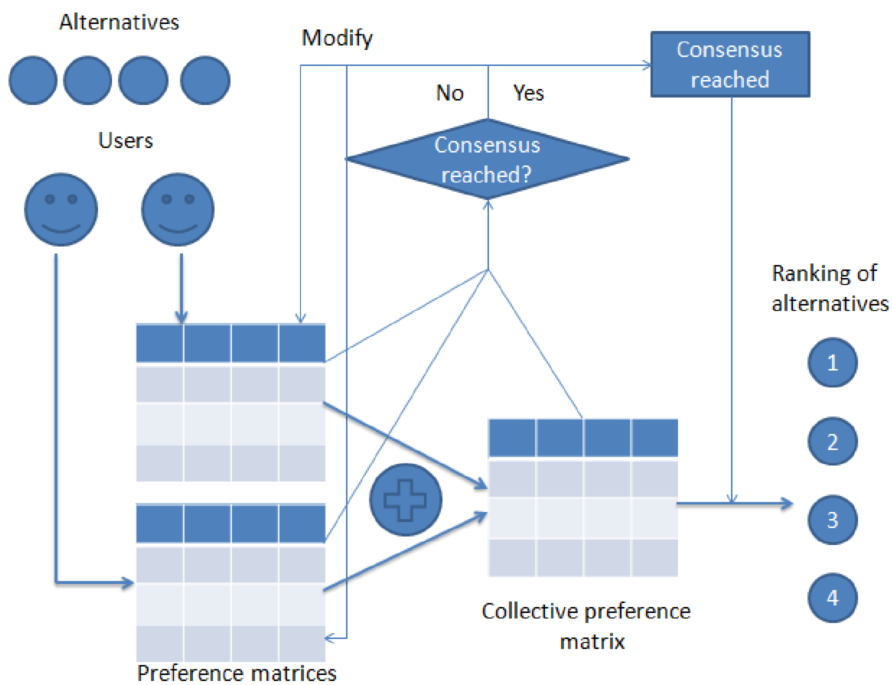

Figure 1: Group Decision Making scheme

- **Calculating final ranking results**: Using the collective preference matrix, selection measures and operators [20, 46] can be used to obtain the final ranking of the alternatives.

GDM methods has gained significant attention in the last decades, with new proposals appearing in the literature continuously. Focusing on recent years, in [31], sentiment analysis is used in order to analyze the GDM processes carried out on the Web. In [26], a comparative study on consensus measures is carried out. In [23], intuitionistic 2-tuple linguistic label sets are used for dealing with multi-attribute GDM environments. In [39], authors present a novel representation for intuitionistic fuzzy systems that they apply on Critical Decision Making. In [7], GDM environments where experts' influence is used to generate recommendations are introduced. In [50], trust propagation among the experts is used in order to develop a visual consensus model for GDM methods that are carried out on social networks. In [5], a method that estimate missing preferences using social influence among the experts is presented. In [6], fuzzy rankings are used in order to rank alternatives in GDM environments. In [24], a three-way decision approach that

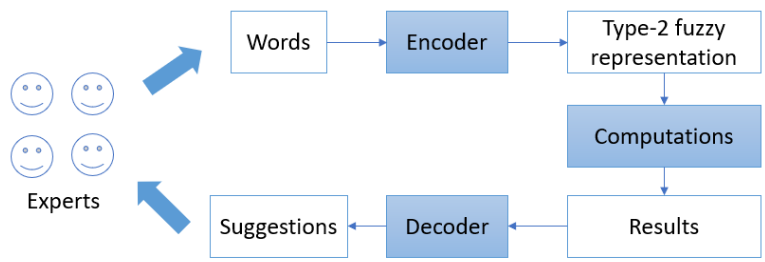

Figure 2: Perceptual computing scheme.

uses intuitionistic fuzzy sets is used to solve multi-attribute decision making problems. In [21], a linguistic scale function that transforms the semantics corresponding to hesitant linguistic terms into the linguistic preference values is proposed. The presented methodology is applied on fire rescue plans. In [12], fuzzy probabilistic rough sets and probability theories are uses in order to assist decision makers in the analysis of intelligent information coming from terrorist groups. Finally, in [51], a consensus model using hesitant fuzzy information and changeable clusters is proposed to deal with situations involving a large number of experts.

2.2. Perceptual Computing scheme using sentiment analysis procedures

Computers and humans use different means for expressing themselves. While computers were built to deal with numerical and exact information, humans tend to express themselves using imprecise and conceptual information. In order to reduce this gap, there is a need for methods that are capable of allowing a computer to extract information from natural language data.

Sentiment analysis procedures [4, 41] try to elucidate the sentiment of the user as expressed in a piece if text. By analyzing the type of words and expressions that a user employs, it is possible to comprehend how he/she feels about the topic that is discussed. Based on this, a system can provide assistance to experts in a luminous way. This data processing approach is called perceptual computing as depicted in Figure 2. Recent contributions focusing on perceptual computing [13, 25, 38].

There are several approaches in the literature to be used for sentiment analysis, including the bag of words approach [47], utilized in this article. A typical bag of words approach includes the following steps as shown in Figure

3:

- **Selecting target sentiments**: A set of sentiments to be detected in the text need to be specified. The analysis can be performed on different levels: (i) focusing on the detection of specific sentiments such as anger, or (ii) determining on a general level whether the user's attitude is positive or negative.

- **Obtaining list of words related to sentiments**: Keeping the goal of the analysis in mind, a list of characterizing words is identified for each sentiment. The words are selected in a way to provide an appropriate representation of experiencing the specific emotion.

- **Analyzing the target texts**: Based on searching the texts for the words generated in the previous step, the number of hits for each sentiment is stored. If the number of hits is above a certain threshold, the writer of the text is considered to express the sentiment when creating the text.

- **Showing final results**: After carrying out the analysis, each of the analyzed texts have zero, one or several sentiments attached.

Sentiment analysis methods are increasingly presented in the literature as applied to problems related to GDM. For instance, in [33], sentiment analysis procedures are used in order to carry out GDM processes directly over the debate texts of the experts. In [11], an ontology for sentiment analysis is built. In [17], a comparison on sentiment analysis approaches is performed and applied to the tourism domain. In [1], successes on developing a hybrid sentiment analysis and future challenges are depicted. Finally, in [44], sentiment analysis is used to detect conflicts in legislative speeches.

2.3. Fuzzy Ontologies

Fuzzy ontologies [49] are an extension of standard ontologies that can be used for representing imprecise information. For this purpose, the fuzzy sets theory is employed. Thanks to fuzzy ontologies, it is possible to represent information in an organized way. Also, it provides us with means that allow us to retrieve information that fulfill a certain set of characteristics. Formally, a fuzzy ontology can be defined as a tuple $< I, C, R, F, A >$ (a graphical representation presented in Figure 4), where:

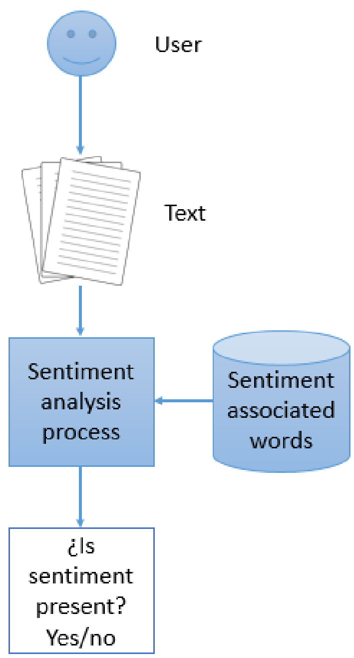

Figure 3: Sentiment analysis scheme.

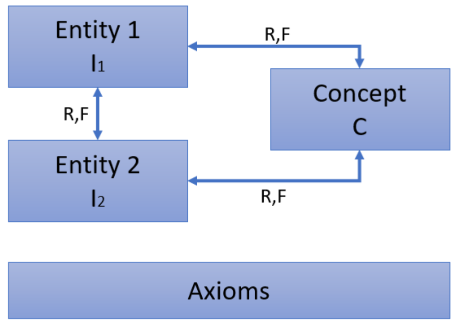

Figure 4: Fuzzy ontology scheme.

- I is the set of entities;
- C is the set of concepts used to describe the set of entities;
- R is the set of crisp relations indicating whether an entity fulfills a concept or not;
- F is the fuzzy relation indicating that an entity fulfills a concept at a certain degree. In this paper we will use hesitant fuzzy linguistic term sets where each label has an associated interval type-2 fuzzy set for this purpose.
- A is the set of axioms describing rules that the elements of the fuzzy ontology must fulfill.

In order to represent the information, each entity is associated to a set of concepts that are applicable to them. Entities are elements that are described in the ontology while concepts are the characteristics associated to them. If a fuzzy ontology relation is used, a value in the interval [0,1] indicating the fulfillment degree is assigned to each entity and concept pair.

Fuzzy ontologies are frequently employed in recent literature. For instance, in [30], an automatic procedure to generate fuzzy ontologies based on Internet opinions is presented. In [45], a review on type-2 fuzzy ontologies is carried out. In [52], a process to store fuzzy ontologies in fuzzy relational databases is shown. Finally, in [19], a formal approach for building fuzzy XML data models based on OWL 2 ontologies is presented.

3. A novel dynamic Group Decision Making with Fuzzy Ontology Support

In this paper, a novel dynamic GDM method with Fuzzy Ontology support for providing a reasonable set of alternatives for the experts to discuss about is presented. In order to carry out this process, the following steps are performed as depicted in Figure 5:

1. **Defining the fuzzy ontology**: A Fuzzy Ontology representation of information about the alternatives to be discussed has to be created.
2. **Extracting information from the debate**: Experts carry out a debate to elucidate which are the desirable characteristics of the alternatives. Debate transcriptions are analyzed using sentiment analysis in order to extract information about the alternatives' requirements.
3. **Generating a reduced set of alternatives**: Using the requirements extracted in the previous step and by performing fuzzy queries, a reduced set of alternatives that better fit the requirements are selected.
4. **Performing GDM computations**: After the experts formulate their preferences, ranking results and consensus measures are calculated for the reduced set of alternatives. If another GDM round is required, the process is repeated from point 2.

3.1. Defining the interval type-2 hesitant fuzzy ontology

As the first step, a fuzzy ontology about the alternatives is constructed. This can be done manually or by defining a conversion process from an existing database. The required fuzzy ontology can be built in the following steps:

- **Defining the entities**: Each alternative is considered as an entity.
- **Defining the concepts**: Each concept is a description about an specific feature of the alternatives. Characteristics that the experts perceive as relevant about the alternatives should be included here.
- **Defining the entity-concept relations**: Relations between entities and concepts represent the way that alternatives fulfill the associated characteristics. In order to promote flexible descriptions based on conceptualization, linguistic label sets can be used. Specifically, each alternative-concept relation is defined as a hesitant linguistic term, i.e.

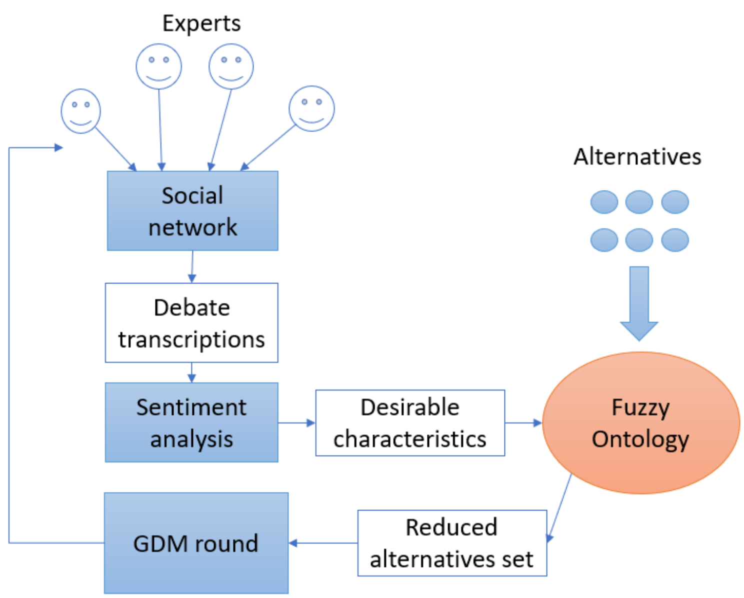

Figure 5: Presented method scheme.

several labels can be attached for each alternative and concept pair. Furthermore, in order to provide flexibility on the labels' definition, interval type-2 fuzzy sets are used. Formally, the relation between alternative x_i and concept c_j, $R(x_i, c_j)$, can be defined using the linguistic label set $S = \{s_1, \ldots, s_g\}$ as follows:

$$R(x_i, c_j) = \{\{s_v, \ldots, s_w\} | v, \ldots, w \in 1, \ldots, g | v \neq w\} \quad (1)$$

Each label is defined as a interval type-2 fuzzy set. An interval type-2 fuzzy set can be formally defined as:

$$\tilde{A} = \{x, UMF(x), LMF(x)\}, \forall x \in X \quad (2)$$

where UMF is the upper membership function and LMF is the lower membership function.

For exemplary purposes, the linguistic label set $S^7 = \{s_1, \ldots, s_7\}$ presented in Table 1 using triangular form notation can used. Our choice of representation is motivated by the extra flexibility provided by type-2 fuzzy sets over standard fuzzy sets.

Label	UMF	LMF
s_1	(0,0,0.1)	(0,0,0.05)
s_2	(0,0.1,0.3)	(0.05,0.1,0.2)
s_3	(0.1,0.3,0.5)	(0.2,0.3,0.4)
s_4	(0.3,0.5,0.7)	(0.4,0.5,0.6)
s_5	(0.5,0.7,0.9)	(0.6,0.7,0.8)
s_6	(0.7,0.9,1)	(0.8,0.9,1)
s_7	(0.9,1,1)	(0.95,1,1)

Table 1: Fuzzy sets used for defining the labels in S.

Depending on the tackled problem, the fuzzy ontology may need to be updated with new information or some entities need to be removed. When this situation appears, the fuzzy ontology must be modified and the chosen alternatives for the discussion must be recalculated according to the new representation.

3.2. Extracting information from the debate of experts

The debate can be initiated once that the fuzzy ontology is constructed. Experts can use a social network or an online forum. In order to obtain the most desirable characteristics for the alternatives from the transcriptions of the debate, sentiment analysis procedures are employed. In this paper, the bag of words sentiment analysis approach depicted in subsection 2.2 will be used. In order to carry out this process, the next steps are followed:

- **Defining lists of positive and negative words**: In the sentiment analysis bag of word approach, several lists of sentiments' related words must be generated in order to track the desired postures. Since our method is tracking opinions, a list of positive and negative words will allow us to identify positive and negative feelings on the alternatives.

- **Classifying the texts according to the alternatives characteristics**: Each concept has an associated keyword list, kw_i that contains words that unambiguously identify the concept. Using this list, one can identify the concept that is mainly referred by each text by analysing the debate transcriptions. Based on this analysis, the system can create the indexed family T, defined as

$$T = \{t_{ij}\} | c_i \in C, e_j \in E \tag{3}$$

where t_{ij} is a set of texts provided by e_j that mention how the c_i should be fulfilled by the alternatives.

- **Searching for positive and negative words in the texts**: Once the classification is performed, words from the positive and negative lists can be searched for in order to determine the desirable characteristics. Thanks to this, it is possible to identify how the experts were feeling when writting each of the texts. For each expert and concept, values $pwcount_{ij}$ and $nwcount_{ij}$ are calculated. They indicate, respectively, the number of times that positive and negative words have been provided by the experts when the characteristic c_i was being mentioned by e_j. Positive words indicate that the expert values positively the characteristic since he/she has positive sentiments about it. On the other way around, negative words indicate that the expert does not like it.

- **Calculating the preference value for each expert and characteristic**: Once that the sentiment analysis procedure have been performed, it is possible to use the *pwcount* and *nwcount* values for calculating a numerical value, p_{ij}, that indicates the level of fulfillment that the alternatives should have about an specific concept:

$$p_{ij} = \frac{pwcount_{ij} - nwcount_{ij}}{pwcount_{ij} + nwcount_{ij}} \tag{4}$$

While this value is in the interval [-1,1], one can obtain a [0,1] representation by carrying out a domain conversion:

$$p'_{ij} = \frac{p_{ij} + 1}{2} \tag{5}$$

- **Obtaining the collective desirable value for c_i**: By aggregating the p_{ij} values for each expert, the desirable value, d_i, for the concept c_i can be calculated as

$$d_i = \sum_{j=1}^{n} w_j \cdot p_{ij} \tag{6}$$

where w is a weighting vector indicating the importance of each expert. In lack of information in a generic case, equal weights can be used for each expert. The d_i values indicate the level of fulfillment of concept c_i that alternatives should have. By using this value, a query over the fuzzy ontology can be specified in order to retrieve a reduced set of alternatives that are closer to the d_i values.

3.3. Generating the reduced set of alternatives for the Group Decision Making round

The query mentioned in the previous step does not have to include all the concept values. In case there are some concepts not mentioned in the debate or insufficient information is provided about them, they can be excluded from the query. In order to formulate the query, the following parameters must be established:

- **Importance given to each concept**: By using $pwcount_{ij}$ and $nwcount_{ij}$, it is possible to measure the importance given to each of the concepts during the debate. Termed as the degree of appearance and denoted as da_i, it can be calculated as

$$da_i = \sum_{j=0}^{n} (pwcount_{ij} + nwcount_{ij}) \tag{7}$$

  The higher the value of da_i is, the more importance the concept had during the debate. In order to compare different degrees of appearance, da_i can be normalized to the [0,1] interval as

$$dan_i = \frac{da_i}{\sum da_i} \tag{8}$$

- **Set of concepts**: The set of concepts that should be included in the query must be determined. For this purpose, one of the following approaches can be selected:

  - **Selecting the λ most mentioned concepts**: By using the da_i values, it is possible to sort the concepts according to the importance that they were given in the discussion and select the λ highest valued concepts for the query.
  - **Using the λ concepts that have an importance value higher than β**: It is possible to establish a threshold, β, based on the da_i values and select only those concepts whose associated value is higher.

- **Number of results, z**: The number of results establishes the number of alternatives that the experts will consider. A number between 3 and 7 is recommended so that the experts do not get lost among too many possibilities and the debate can be carried out in a comfortable and efficient way.

- **Establishing the weights of selected concepts**: Expression (8) can be applied over the set of selected concepts in order to calculate the associated weights.

Once the set of weights, W, and set the of selected concepts, $C = \{c_1, \ldots, c_o\}$ have been calculated, it is possible to retrieve the set of α alternatives that fulfill the experts' requirements the most. For this purpose, a similarity value for each alternative according to the query, Q, is calculated as follows:

$$s(x_i, Q) = \phi(sim(d_i, R(x_i, c_j)))|\forall j \in [1, o] \tag{9}$$

where ϕ is the mean operator and $sim(d_i, R(x_i, c_j))$ can be calculated as follows:

$$sim(d_i, R(x_i, c_j)) = \phi(max(\mu_h(d_i, c_j))) \tag{10}$$

where $\mu_h(d_i, c_j)$ is the set of intervals that are obtained after calculating the membership value of d_i to all the interval type-2 fuzzy sets that are associated to the labels of the relation $R(x_i, c_j)$. Once that the similarity values $s(x_i, Q)$ have been calculated and sorted, a set with the α most appropriate alternatives can be generated.

3.4. Carrying out the dynamic Group Decision Making process

In order to rank the generated reduced set of alternatives, the scheme described in subsection 2.1 can be employed. The steps that must be followed are described in more detail below:

1. **Providing preferences**: Experts provide preferences using preference relation matrices. Value p_{ij}^k indicates how much e_k prefers x_i over x_j. In order to allow the experts to provide preferences in a comfortable way, the linguistic label set $S = \{s_1, \ldots, s_7\}$ can be used. Each expert may select the linguistic label set that he/she prefers if multi-granular fuzzy linguistic modelling procedures [29, 35] are used.
2. **Calculating the collective preference matrix**: Preferences provided by the experts can be aggregated to obtain a collective preference matrix. Intervals defining the fuzzy sets of the labels provided are aggregated in order to generate a collective preference matrix where an

interval is assigned to each pair of alternatives. The intervals are generated by calculating the mean between UMF and LMF membership values for each label. For this purpose, the following expression can be used:

$$c_{ij} = \sum_{k=1}^{n} \phi(p_{ij}^k) \tag{11}$$

where ϕ represents the mean operator over the labels associated intervals.

3. **Calculating consensus measures [26]**: Measuring consensus will allow us to determine whether another GDM round should be carried out or an agreement is reached. First, similarity between each expert, e_k, and the collective group is calculated as

$$sm_{ij}^k = sim(p_{ij}^k, c_{ij}) \tag{12}$$

where sim refers to a similarity function. For exemplary purposes, the 1-norm distance can be used. The consensus matrix is calculated by aggregating all the obtained sm_{ij}^k values as follows:

$$\forall i, j \in [1, m]; cm_{ij} = \phi(sm_{ij}^1, \ldots sm_{ij}^n) \tag{13}$$

By using cm, it is possible to measure consensus at three different levels:

- **Pair of alternatives level**: Measures the agreement that experts have when comparing two different alternatives. It can be calculated as follows:

$$cp_{ij} = cm_{ij} \tag{14}$$

- **Alternatives level**: Measures the agreement that experts have on a specific alternative. It is calculated as stated below:

$$ca_i = \phi(cp_{ij}, cp_{ji}; j = 1 \ldots m \wedge j \neq i) \tag{15}$$

- **Global consensus level**: By aggregating all the ca_i values, it is possible to obtain an overall consensus value for the GDM round:

$$cr = \phi(ca_i; i = 1 \ldots m) \tag{16}$$

4. **Calculating the ranking of alternatives**: In order to calculate the rankings, the mean between guided dominance and guided non dominance degree operators, GDD and GNDD respectively, can be used. GDD and GNDD operator expressions are defined as:

$$GDD_i = \phi(c_{i1}, c_{i2}, \dots, c_{i(i-1)}, c_{i(i+1)}, \dots, c_{in}) \tag{17}$$

$$GNDD_i = \phi(c^s_{1i}, c^s_{2i}, \dots, c^s_{(i-1)i}, c^s_{(i+1)i}, \dots, c^s_{ni}) \tag{18}$$

   where

$$c^s_{ji} = \max\{c_{ji} - c_{ij}, 1\}$$

   The final ranking of alternatives can be calculated as the mean of the calculated values:

$$RV_i = (GDD_i + GNDD_i)/2, \forall i \in [0, m] \tag{19}$$

   It is important to note that in our model, these operators are applied over intervals. In order to rank the alternatives according to the obtained RV_i values, the intervals' centroids can be used.

5. **Modifying the set of experts**: At any time of the process, any expert can join or leave. When an expert abandons the process, his/her preferences are deleted from the system and the ranking needs to be recalculated using only the texts of the remaining experts. Therefore, the actual GDM round stops and the GDM process goes back to the *generating the reduced set of alternatives* step depicted in subsection 3.3. The reduced ranking of alternatives is recalculated and the process continues from there. New experts can also join the debate at any time of the process. In this case, the actual GDM round stops and it goes back to the *extracting information from the debate of experts* step depicted in subsection 3.2. The debate on the characteristics is restarted and the new experts share their opinion with the ones that were there before. The process continues from there as usual.

4. Illustrative Example

In this section an example application of the proposed method is presented. In the example, we assume that a political party needs to decide which candidate should be nominated for an upcoming election. At the start

Concept	**Description**	x_1	x_2	x_3
c_1	Charisma	$\{s_1, s_2\}$	$\{s_6, s_7\}$	$\{s_4, s_5\}$
c_2	Communication	$\{s_5, s_6, s_7\}$	$\{s_1, s_2\}$	$\{s_5, s_6\}$
c_3	Honesty	$\{s_4, s_5, s_6\}$	$\{s_6, s_7\}$	$\{s_3, s_4\}$
c_4	Scandal resistance	$\{s_6, s_7\}$	$\{s_1, s_2\}$	$\{s_3, s_4\}$
c_5	Intelligence	$\{s_2, s_3\}$	$\{s_1, s_2\}$	$\{s_2, s_3\}$
c_6	Diplomacy	$\{s_1, s_2\}$	$\{s_6, s_7\}$	$\{s_2, s_3\}$
c_7	Passion	$\{s_4, s_5\}$	$\{s_5, s_6\}$	$\{s_2, s_3\}$
c_8	Humor	$\{s_2, s_3\}$	$\{s_6, s_7\}$	$\{s_5, s_6\}$
c_9	Thoughtfulness	$\{s_5, s_6\}$	$\{s_6, s_7\}$	$\{s_4, s_5\}$
c_{10}	Bravery	$\{s_5, s_6\}$	$\{s_4, s_5\}$	$\{s_3, s_4\}$

Table 2: Descriptions of the fuzzy ontology concepts along with some relation examples.

of the process, there are 25 candidates $X = \{x_1, \ldots, x_{25}\}$ that should be evaluated and ranked by a set of 4 experts, $E = \{e_1, e_2, e_3, e_4\}$. Information about 10 different characteristics of the candidates, $C = \{c_1, \ldots, c_{10}\}$, is available. In Table 2, descriptions of the concepts along with relation values that they have for alternatives x_1, x_2 and x_3 are shown. In this example, consensus threshold is set to 0.75. When the global consensus value becomes higher, it implies that the experts have reached an agreement and the GDM process can end.

Experts carry out a debate in which they discuss about the desirable characteristics. The transcriptions of the debate texts are sorted according to the characteristic that they refer. Next, the number of positive and negative words that experts use is calculated. The four most used characteristics will be employed in order to retrieve the reduced set of alternatives. After counting the number of word matches, this set is compound by $\{c_2, c_4, c_7, c_8\}$. The number of positive and negative words provided by the experts about those concepts is shown in Table 3. By using expressions (4) and (6), it is possible to calculate the most desirable value for each of the concepts. Results are shown in Table 4. For instance, for e_2 and c_2, p value is computed as follows:

$$p_{21} = \frac{7-1}{8} = 0.75$$

Experts	c_2		c_4		c_7		c_8	
	+	-	+	-	+	-	+	-
e_1	7	0	6	1	0	4	5	1
e_2	7	1	7	2	1	5	7	1
e_2	4	3	8	2	0	4	8	1
e_4	6	1	10	1	2	1	10	2

Table 3: Number of positive and negative words provided by the experts for the most discussed characteristics.

Experts	c_2	c_4	c_7	c_8
e_1	1	0.8571	0	0.833
e_2	0.875	0.7777	0.1666	0.875
e_2	0.5714	0.8	0	0.888
e_4	0.8571	0.909	0.6666	0.833
d_i	0.8258	0.836	0.2083	0.857

Table 4: Calculation of the desirable values.

In order to normalize the value, expression (5) is used as follows:

$$p'_{21} = \frac{0.75 + 1}{2} = 0.875$$

In these calculations we consider all the experts having the same impact on the process.

By using the number of times that concepts were mentioned in the debate, expression (8) can be used in order to determine the weight that each concept must have on the query. The obtained concept weighting vector is calculated as

$$W = \{0.2457, 0.3135, 0.1441, 0.2966\}$$

Once the d_i values and their associated weighting vector is calculated, similarity values between each of the alternatives and the query can be calculated. Results for the eight closest alternatives are shown in Table 5.

After analyzing the query results, experts decide to carry out the GDM process using the three most valued candidates. Therefore, $\{x_{25}, x_{21}, x_3\}$ are the chosen alternatives. First, the experts provide their preferences using a

Alternative	Similarity value
x_{25}	0.5196
x_{21}	0.4104
x_3	0.3565
x_{13}	0.3172
x_{10}	0.3115
x_5	0.2929
x_1	0.2722
x_{23}	0.2525

Table 5: Similarity values result.

matrix:

$$P^1 = \begin{pmatrix} - & s_7 & s_6 \\ s_3 & - & s_2 \\ s_1 & s_1 & - \end{pmatrix} P^2 = \begin{pmatrix} - & s_6 & s_7 \\ s_3 & - & s_3 \\ s_1 & s_2 & - \end{pmatrix}$$
$$P^3 = \begin{pmatrix} - & s_7 & s_7 \\ s_4 & - & s_3 \\ s_2 & s_1 & - \end{pmatrix} P^4 = \begin{pmatrix} - & s_6 & s_6 \\ s_2 & - & s_1 \\ s_1 & s_1 & - \end{pmatrix}$$

By calculating the interval from the aggregation of UMF and LMF membership values, the following results are obtained:

$$P^1 = \begin{pmatrix} - & [0.925, 1] & [0.75, 1] \\ [0.15, 0.45] & - & [0.025, 0.25] \\ [0, 0.075] & [0, 0.075] & - \end{pmatrix}$$
$$P^2 = \begin{pmatrix} - & [0.75, 1] & [0.925, 1] \\ [0.15, 0.45] & - & [0.15, 0.45] \\ [0, 0.075] & [0.025, 0.25] & - \end{pmatrix}$$
$$P^3 = \begin{pmatrix} - & [0.925, 1] & [0.925, 1] \\ [0.35, 0.65] & - & [0.15, 0.45] \\ [0.025, 0.25] & [0, 0.075] & - \end{pmatrix}$$
$$P^4 = \begin{pmatrix} - & [0.75, 1] & [0.75, 1] \\ [0.025, 0.25] & - & [0, 0.075] \\ [0, 0.075] & [0, 0.075] & - \end{pmatrix}$$

After aggregating all the matrices, the following collective preference matrix

	x_{25}	x_{21}	x_3
GDD	[0.725,0.8333]	[0.25,0.41]	[0.1708,0.2458]
GNDD	1	[0.777,0.816]	[0.6437,0.6979]
Ranking	[0.8625,0.9166]	[0.5135,0.6177]	[0.4343,0.4447]

Table 6: Ranking results for the alternatives.

is obtained:

$$C = \begin{pmatrix} - & [0.8375, 1] & [0.8375, 1] \\ [0.16875, 0.45] & - & [0.08125, 0.30] \\ [0.00625, 0.11875] & [0.00625, 0.11875] & - \end{pmatrix}$$

Once the collective matrix has been calculated, it is possible to obtain the ranking of alternatives by applying GDD and GNDD operators as shown in Table 6. It can be seen that the ranking is $\{x_{25}, x_{21}, x_3\}$, x_{25} being the most voted alternative.

Finally, consensus results are calculated in order to determine whether experts have reached a sufficient agreement level. First of all, CM matrix is calculated by using (13). This matrix shows the consensus reached for each pair of alternatives. It should be taken into account that the presented values are expressed in the interval [0,1] with 1 indicating total consensus. The result of this calculation is the following:

$$CM = \begin{pmatrix} - & [0.9125, 1] & [0.7437, 1] \\ [0.9, 0.9093] & - & [0.8562, 0.9312] \\ [0.9343, 0.9906] & [0.9125, 0.9906] & - \end{pmatrix}$$

Afterwards, expression (15) is applied in order to calculate the consensus for each alternative:

$$CA = \{[0.9171, 0.95], [0.9515, 0.9562], [0.8375, 0.9281]\}$$

Finally, values from vector ca can be aggregated in order to calculate the global consensus for the decision round as the interval [0.913,0.933]. Since the (centroid of the) obtained consensus interval is above the established threshold, 0.75, then there is no need for carrying out any more GDM rounds.

In case another GDM round was needed, experts would carry out another debate. From that debate, a new set of desirable characteristics for the alternatives could be obtained. A new reduced set of alternatives would be generated by using the information provided. Finally, the exposed GDM process could be repeated using the new set of alternatives. The more that the experts communicate among themselves, the more points of views are shared making the extracted information more accurate and supported by the whole set of experts. This would result in a more reliable reduced set of alternatives for the experts to rank.

Considering another possible situation, we can assume that while the experts are debating, candidate x_3 leaves the election and another two candidates, x_{26} and x_{27}, join the process. If this happen, there is a need to stop the process and recalculate the candidates ranking. In this new environment, the five most voted candidates could be $\{x_{25}, x_{21}, x_{13}, x_{10}, x_5\}$. Therefore, candidate x_3 is replaced by x_{13} in the discussion and the GDM debate is restarted.

5. Discussion

In this paper, a novel dynamic GDM method for dealing with environments with a high number of alternatives is presented. A perceptual computing scheme is used in order to extract information directly from the debate. Sentiment analysis is employed in order to extract the desirable characteristics of the alternatives. Finally, a fuzzy ontology is used in order to store the information from the alternatives and obtain the reduced set of alternatives that the experts will rank. The proposed method presents the following advantages:

- **Information is extracted directly from the debate**: Most of the available methods in literature use preferences directly provided by the experts. Although it is a good approach, debate transcription contains more information about what the experts really think. Therefore, by using debate transcriptions, less information is wasted. Our method presents a novel method that uses a perceptual computing approach that employs sentiment analysis in order to extract information directly from the debate. Consequently, a reduced set of alternatives is generated using all the valuable information shared by the experts.

- **A novel relation type in the Fuzzy Ontology**: The information that is available on the Internet and that the experts provide in the debate is imprecise and expressed using free text. In this paper, a novel type of fuzzy relation is presented. Thanks to the presented hesitant type-2 fuzzy scheme, it is possible to assign several labels to each entity-concept relation. This way, the representation capability of the fuzzy ontology is boosted. Thanks to type-2 fuzzy sets, the inner representation of each label is also more flexible compared to normal fuzzy sets.

- **Experts and alternatives can vary during the process**: Recent GDM methods are carried out over the Web. This new communication mean promotes a flexible scheme where experts and alternatives can appear or be removed at any time. The presented method takes this into account and allows experts to be added and removed. In each step, a new set of alternatives is selected by taking into account the debate information carried out in the GDM round.

- **The process can generate a reduced set of alternatives**: Human mind can only deal with a small amount of information at the same time. Therefore, we need methods that can adapt information in a way that the experts can carry out a comfortable discussion. Using fuzzy ontologies and sentiment analysis, it is possible to extract information from the debate and carry out a query in order to determine the most desirable alternatives. By using this information, a reduced set of alternatives is generated. This process prevents experts from having to deal with large amounts of information. Since all the alternatives are ranked according to their similarity with the information extracted from the debate, it is possible to choose any number of alternatives to be included in the debate.

The method's main drawback relates to generating the fuzzy ontology. Although a large amount of information is available on Internet about almost any topic, there is a need to define a transformation process that converts that information into the required fuzzy ontology representation. Some guidelines about how to define this process can be found in [34].

In recent literature, some related methods can be found. Fuzzy ontologies have been used as a support system in some articles [8, 37, 42]. Although these articles use fuzzy ontologies in order to generate recommendations, they do not take into account a generic environment where experts can join or leave any time. Furthermore, these contributions focus on solving a specific problem, such as wine selection. Additionally, all these articles use fuzzy ontologies where each concept represents a specific label of a linguistic label set. This makes the fuzzy ontologies difficult to read, define and interpret and they have less representation flexibility than the novel model that is presented in this article. The presented fuzzy hesitant type-2 fuzzy relation makes the entities-concepts relations quite intuitive and easy to read and interpret to human beings as labels are directly assigned to the relations. Another important issue that distinguishes this article from previous research is that the set of alternatives can be updated in each round. This way, the set of alternatives is adapted to the changes of mind that can appear in the GDM debate.

One can also identify research in the literature that deals with the problem of large amount of alternatives without using fuzzy ontologies. For instance, in [36], card sorting techniques are used in order to allow the experts to create groups of alternatives to discuss about. The main drawback of this method is that it forces the experts to manage all the alternatives. In our method, experts only need to discuss about the alternatives characteristics. Consequently, they do not need to directly deal with every available alternative.

As it can be seen, the number of papers dealing with GDM methods with a large number of alternatives is not broad. Recent research on the topic [40, 54] is more focused on dealing with a high number of experts leaving criteria and alternatives set as reduced as in traditional GDM literature. Nevertheless, due to the large amount of information that is now available on the Internet, the development of methods that are capable of dealing with and help experts to process and discuss high number of alternatives are needed.

There is also research on dynamic GDM methods [22, 32] that allows the set of experts and alternatives to be modified at any time. Nevertheless, these methods focus on dealing with dynamic environments and do not consider the problems associated with large amount of information.

Although in [32], the described method works with high number of alternatives and experts, it does not consider any information related to the alternatives. Therefore, experts must find this information and get an idea about how to rank them on their own. In our new method, fuzzy ontologies help the experts to carry out an organized debate by managing all the alternatives related information. It is important to include tools that allow experts to manage all the alternative related information because, specially in environments where there is a high number of alternatives, experts can get lost among all the available data. This can lead to poor decision results due to the incapability of the experts to process all the information on their own.

It is also important to notice that there is little research on the application of sentiment analysis over GDM methods that employ tools to manage high amounts of information. Thanks to sentiment analysis, there is no need of an extra step where the experts have to explicitly provide the desirable characteristics of the alternatives to the system. This information is directly obtained from the debate. Also, this feature allows experts to share information in common language making the process much more comfortable for them. It should be noticed that improving human-computer communication and reducing the number of actions that experts must perform is critical in order to design GDM methods that correctly works in complex environments where participants may get lost due to the high amount of information that they have to deal with. Neither of the previous methods include this feature.

6. Conclusions

In this paper, a novel method to carry out dynamic GDM processes with a high number of alternatives has been presented. Since discussing all the alternatives at the same time is not possible for the experts, fuzzy ontologies are employed in order to assist them in the selection of a reduced set of alternatives to discuss about. In the presented method, experts do not have to directly provide their preferences to the fuzzy ontologies. Instead, sentiment analysis procedures are used in order to analyze the experts' debates and extract the most desirable set of alternatives. This way, the amount of information that experts need to provide to the system is small. Since all the debate transcriptions are analyzed, the system has access to all the information provided during the debate.

In order to increase the imprecision representation capability of the fuzzy ontology, relations between entities and concepts were designed as hesitant fuzzy linguistic term sets and labels are defined using interval type-2 fuzzy sets. Thanks to this, more than one label can be assigned to each relation. This improves the original fuzzy ontology representation capability.

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***conflict of Interest Statement**

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

CRediT author statement

Juan Antonio Morente Molinera → conceptualization, methodology, formal analysis, software, validation, writing-original draft, investigation, data curation, visualization.

Francisco Javier Cabrerizo → methodology, visualization.

Jozsef Mezei → visualization, validation, supervision.

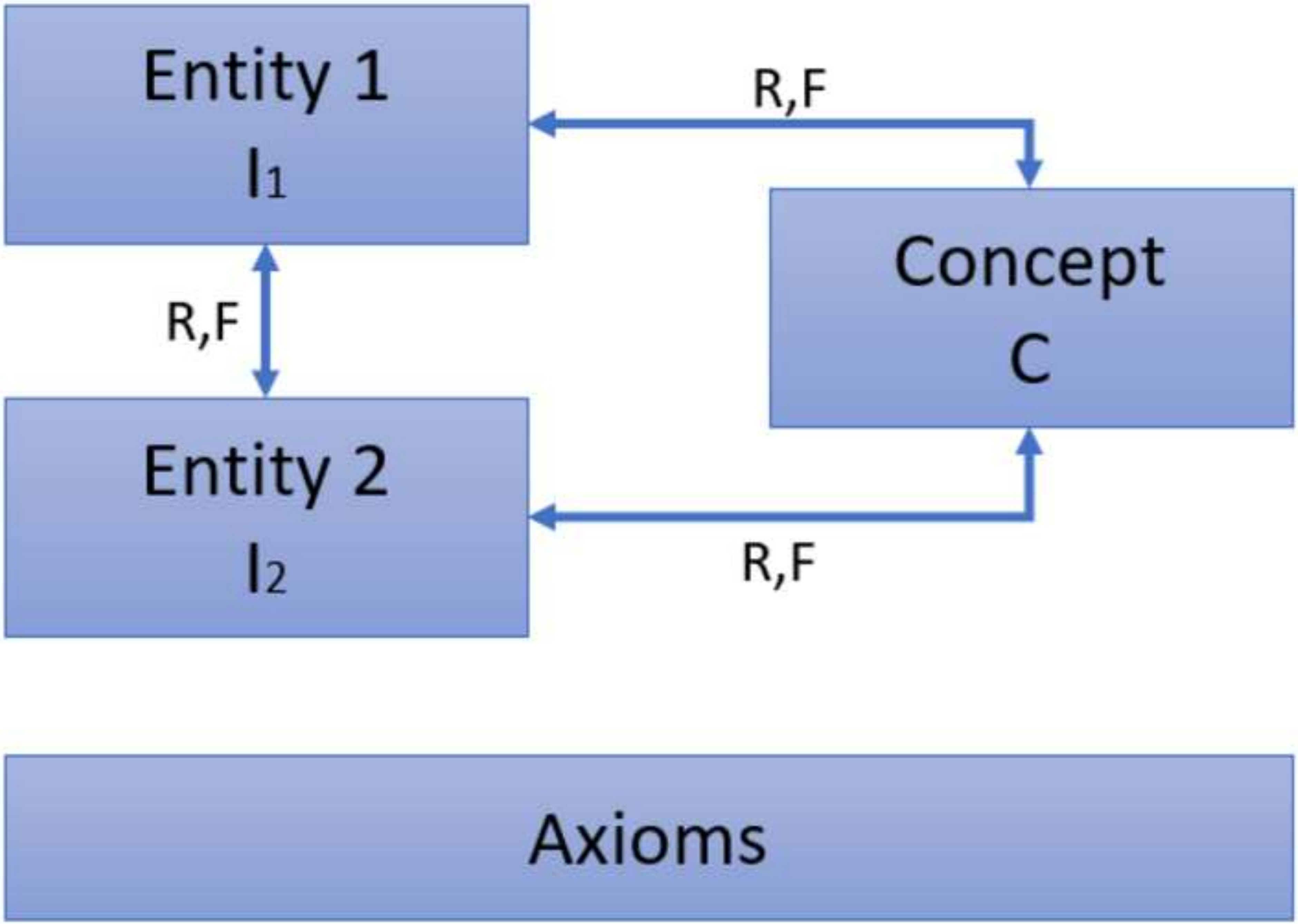
Christer Carlsson → conceptualization, formal analysis, supervision.

Enrique Herrera-Viedma → Writing - Review & Editing, supervision, funding acquisition.

Highlights

- A novel Group Decision Making model for high number of alternatives.
- Sentiment analysis is used for extracting information directly from debate.
- A novel fuzzy ontology model is presented.
- Interval type-2 fuzzy sets are used for increasing flexibility in representation.

Figure(s)



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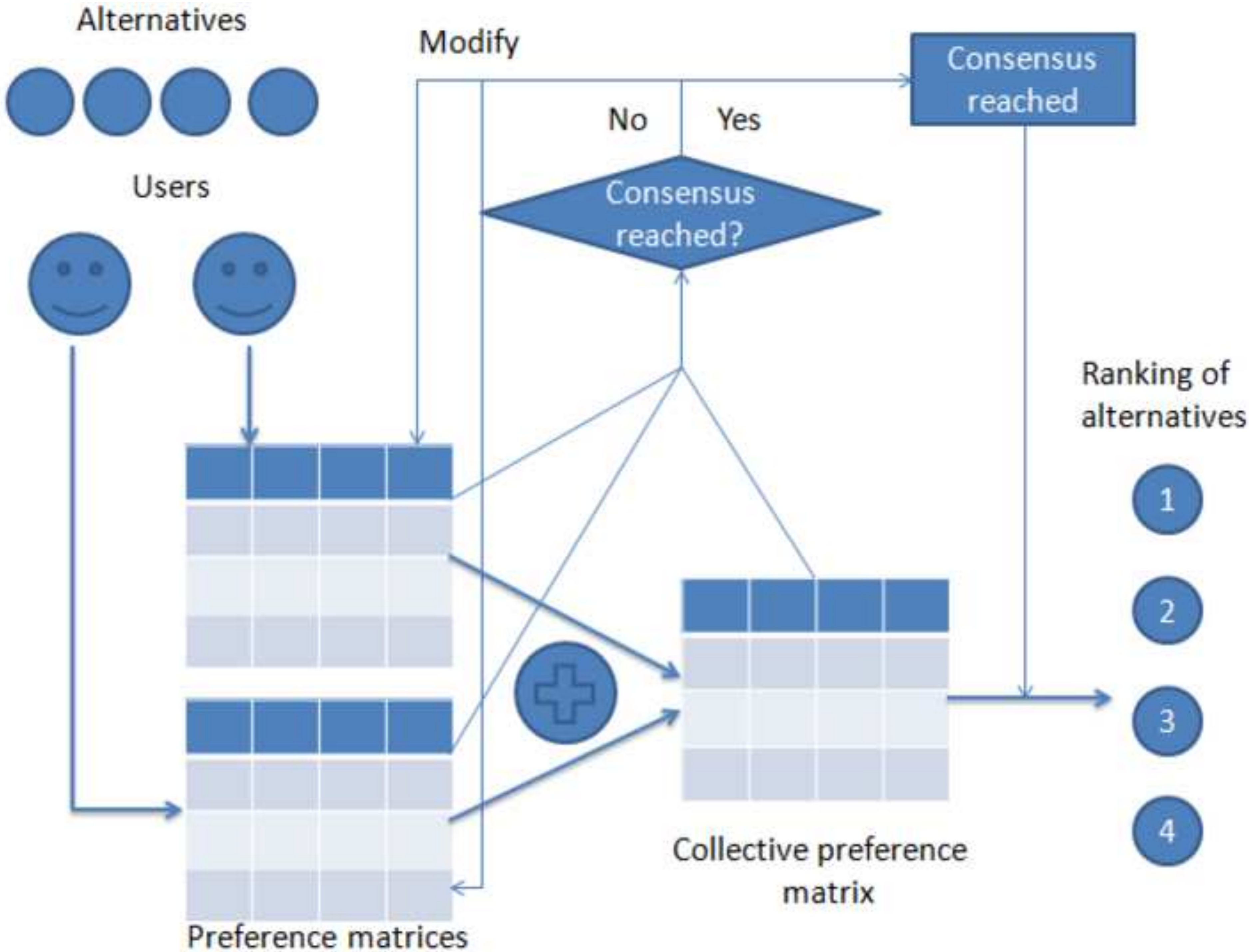
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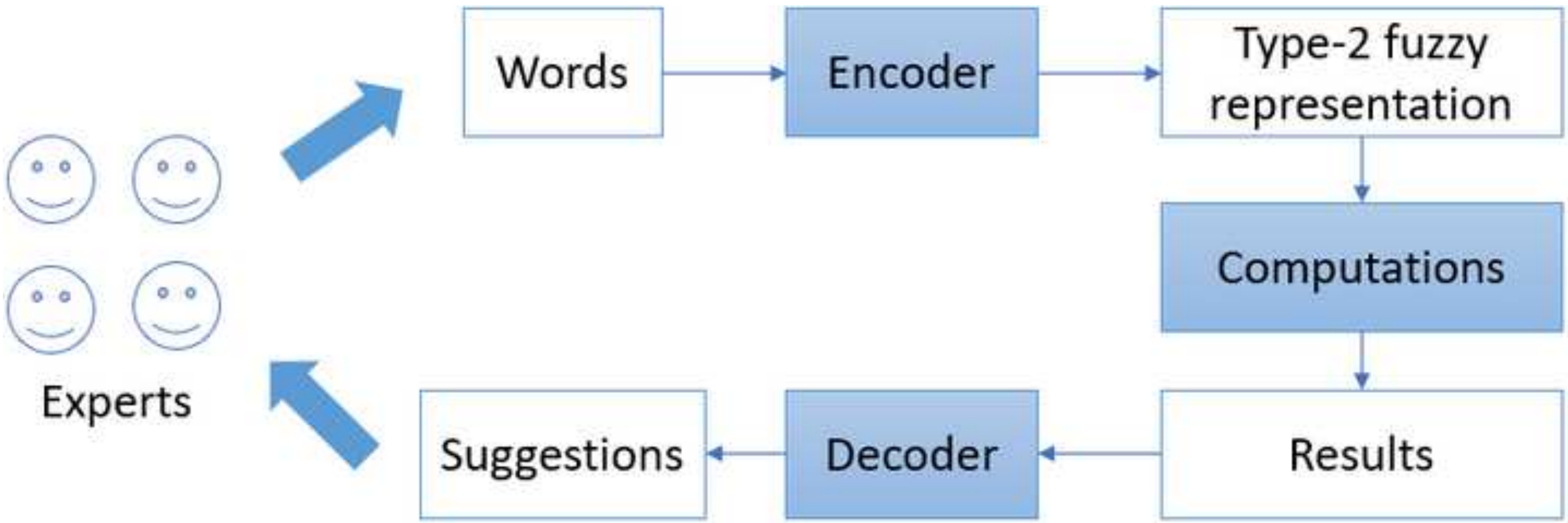
Yes
Users
Consensus reached?
Ranking of alternatives
1
2
3
4
Collective preference matrix
Preference matrices

Figure(s)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Suggestions
Experts

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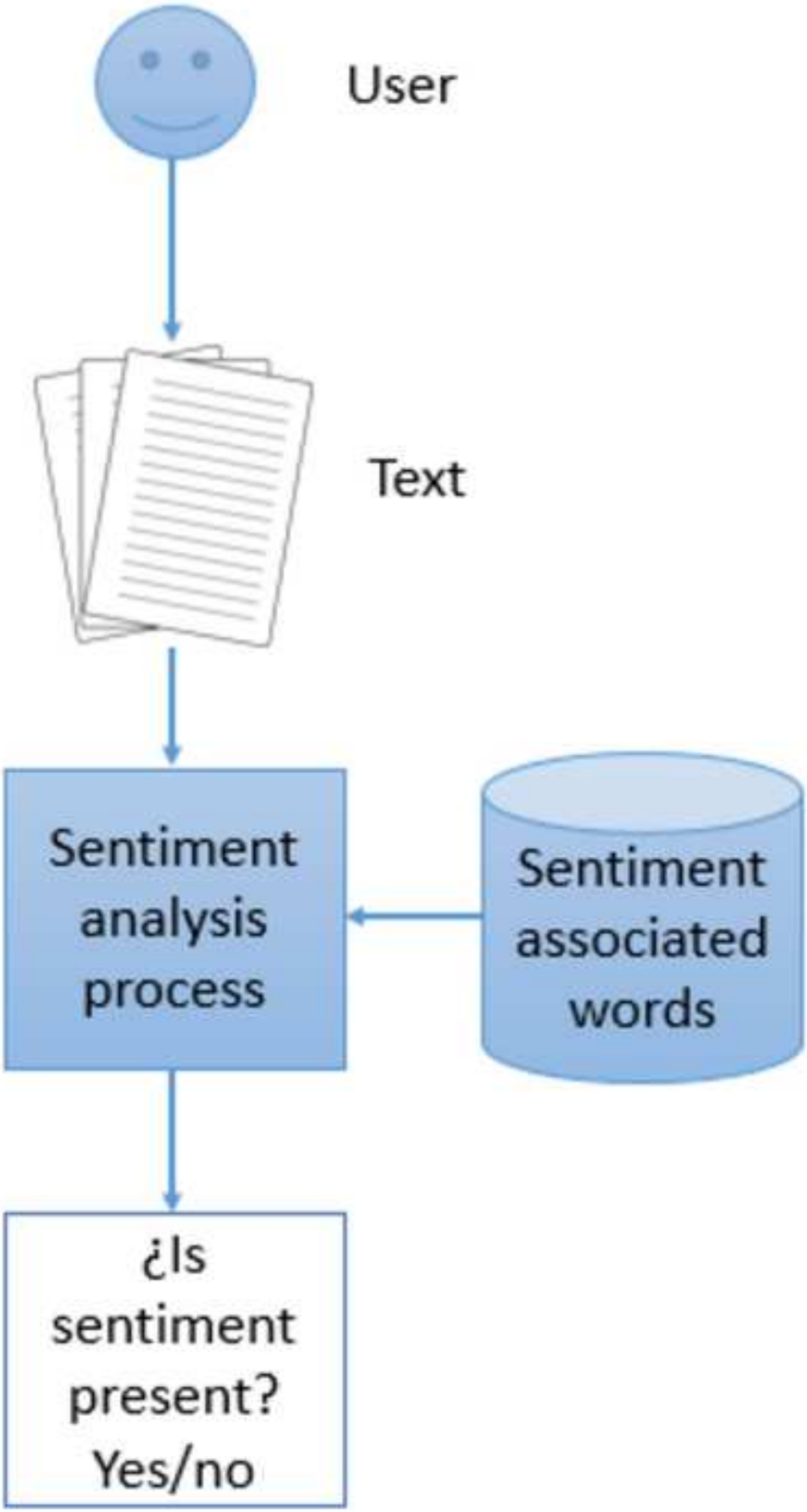
User
Text
Sentiment analysis process
Sentiment associated words
¿Is sentiment present? Yes/no

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