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Enrique Herrera-Viedma • José Luis García-Lapresta • Janusz Kacprzyk
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Consensual Processes

The word consensus has been frequently used for centuries, perhaps millenia. People have always deemed it important that decisions having a long lasting impact on groups, countries or even civilizations be arrived at in a consensual manner. Undoubtedly the complexity of modern world in all its social, technological, economic and cultural dimensions has created new environments where consensus is regarded desirable. Consensus typically denotes a state of agreement prevailing in a group of agents, human or software. In the strict sense of the term, consensus means that the agreement be unanimous. Since such a state is often unreachable or even unnecessary, other less demanding consensus-related notions have been introduced. These typically involve some graded, partial or imprecise concepts. The contributions to this volume define and utilize such less demanding - and thus at the same time more general - notions of consensus. However, consensus can also refer to a process whereby the state of agreement is reached. Again this state can be something less stringent than a complete unanimity of all agents regarding all options. The process may involve modifications, resolutions and /or mitigations of the views or inputs of individuals or software agents in order to achieve the state of consensus understood in the more general sense. The consensus reaching processes call for some soft computational approaches, methods and techniques, notably fuzzy and possibilistic ones. These are needed to accommodate the imprecision in the very meaning of some basic concepts utilized in the definition of consensus as a state of agreement and as a process whereby this state is to be reached. The overall aim of this volume is to provide a comprehensive overview and analysis of the issues related to consensus states and consensual processes.

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Springer

Consensual Processes Based on Mobile Technologies and Dynamic Information

I.J. Pérez, F.J. Cabrerizo, M.J. Cobo, S. Alonso, and E. Herrera-Viedma

Abstract. The aim of this contribution is to present a prototype of decision support system based on mobile technologies and dynamic information. Users can run the system on their own mobile devices in order to provide their preferences at anytime and anywhere. The system provides consensual and selection support to deal with dynamic decision making situations. Furthermore, the system incorporates a mechanism that allows to manage dynamic decision situations in which some information about the problem is not constant through the time, it gives more realism to decision processes with high or dynamic set of alternatives, focussing the discussion in a subset of them that changes in each stage of the process. The experts' preferences are represented using a linguistic approach. In such a way, we provide a new linguistic framework, that is mobile and dynamic, to deal with group decision making problems.

1 Introduction

Group Decision Making (GDM) arises from many real world situations [28, 42]. Thus, the study of decision making is necessary and important not only in Decision Theory but also in areas such as Management Science, Operations Research,

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Politics, Social Psychology, Artificial Intelligence, Soft Computing, and so on. In these situations, there is a problem that can be solved in different ways and a group of experts trying to achieve a consensual solution. To do this, experts have to express their preferences by means of a set of assessments over a set of alternatives.

In the last years, the interaction human-technology has had several significant advances. The spread of mobile devices has increased accessibility to data and, in turn, influenced the time and the way in which users make decisions. Users can make real-time decisions based on the most up-to-date data accessed via wireless devices, such as portable computers, mobile phones, and personal digital assistants (PDAs). So, the application of the latest technologies extends opportunities and allows to carry out consensual processes in new frameworks. We assume that if the communications are improved the decisions will be upgraded, because people can focuss on the problem with less wasted time on unimportant issues [31, 43].

Several authors have provided interesting results on GDM with the help of fuzzy theory [10, 17, 27, 28, 29, 30, 37]. There are decision situations in which the experts' preferences cannot be assessed precisely in a quantitative form but may be in a qualitative one, and thus, the use of a *linguistic approach* is necessary [3, 4, 5, 16, 19, 26, 45, 50]. The *linguistic approach* is an approximate technique which represents qualitative aspects as linguistic values by means of *linguistic variables*, that is, variables whose values are not numbers but words or sentences in a natural or artificial language [15].

In this chapter we present a prototype of mobile decision support system (DSS) to deal automatically with linguistic GDM problems based on mobile technologies. This mobile DSS allows to develop dynamic consensual processes. In fact, at every stage of the decision process, users, in order to reach a common solution, receive recommendations to help them to change their preferences and they are able to send their updated preferences at any moment. Additionally, to better simulate real decision making processes, the mobile DSS includes a tool to manage dynamic sets of alternatives [38], that is, not only dynamic addition of new alternatives that, due to some dynamic external factors, can appear during the decision process, but also deleting some of them considered good alternatives at the beginning of the process but not so later on or are unavailable at the time.

In order to do this, the paper is set out as follows. Some preliminary aspects about GDM models, linguistic approach and mobile technologies usage in GDM problems are presented in Section 2. Section 3 defines the prototype of a mobile DSS and Section 4 includes a practical experiment. Finally, in Section 5 we point out our conclusions.

2 Preliminaries

In this section we present some considerations about GDM problems, the fuzzy linguistic approach and the use of mobile technologies in consensual processes.

2.1 GDM Problems

In a GDM problem we have a finite set of feasible alternatives. $X = \{x_1, x_2, \ldots, x_n\}$, $(n \geq 2)$ and the best alternatives from X have to be identified according to the information given by a set of experts, $E = \{e_1, e_2, \ldots, e_m\}$, $(m \geq 2)$.

Resolution methods for GDM problems are usually composed by two different processes [19] (see Figure 1):

1. *Consensus process:* Clearly, in any decision process, it is preferable that the experts reach a high degree of consensus on the solution set of alternatives. Thus, this process refers to how to obtain the maximum degree of consensus or agreement among the experts on the solution alternatives.
2. *Selection process:* This process consists in how to obtain the solution set of alternatives from the opinions on the alternatives given by the experts. Furthermore, the selection process is composed of two different phases:

    a. Aggregation phase: This phase uses an aggregation operator in order to transform the individual preferences on the alternatives into a collective preference.
    b. Exploitation phase: This phase transforms the collective preference into a partial ranking of alternatives that helps to make the final decision.

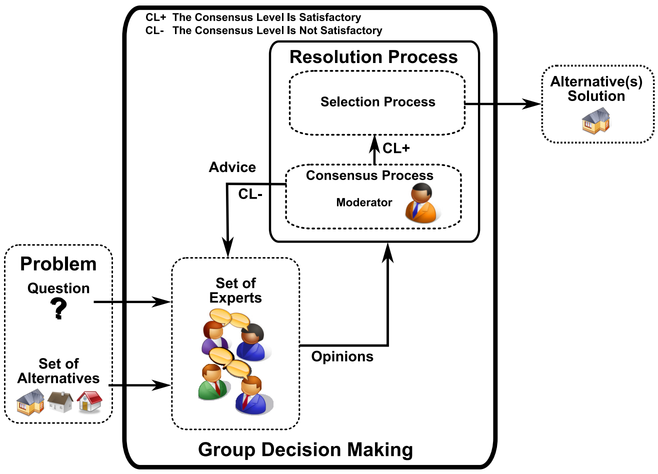


Fig. 1 *Resolution process of a GDM*

2.2 Fuzzy Linguistic Approach

There are situations in which the information cannot be assessed precisely in a quantitative form but may be in a qualitative one. For example, when attempting to qualify phenomena related to human perception, we are often led to use words in natural language instead of numerical values, e.g. when evaluating quality of a restaurant, terms like *good*, *medium* or *bad* can be used. In other cases, precise quantitative information cannot be stated because either it is unavailable or the cost for its computation is too high and an "approximate value" can be applicable, eg. when evaluating the speed of a car, linguistic terms like *fast*, *very fast* or *slow* can be used instead of numeric values [3, 13]. The use of Fuzzy Sets Theory has given very good results for modelling qualitative information [49].

Fuzzy linguistic modelling is a tool based on the concept of linguistic variable to deal with qualitative assessments. It has proven its usefulness in many problems, e.g., in decision making, quality evaluation, information retrieval models, etc[12, 23, 24, 33, 34, 39, 40]. Ordinal fuzzy linguistic modelling [15] is a very useful kind of fuzzy linguistic approach proposed as an alternative tool to the traditional fuzzy linguistic modelling which simplifies the computing with words process as well as linguistic aspects of problems. It is defined by considering a finite and totally ordered label set $S = \{s_i\}, i \in \{0,...,g\}$ in the usual sense, i.e., $s_i \geq s_j$ if $i \geq j$, and with odd cardinality (usually 7 or 9 labels). The mid term represents an assessment of "approximately 0.5", and the rest of the terms are placed symmetrically around it. The semantics of the label set is established from the ordered structure of the label set by considering that each label for the pair (s_i, s_{g-i}) is equally informative [3]. For example, we can use the following set of seven labels to represent the linguistic information:

$S = \{$ N=*Null*, VL=*Very Low*, L=*Low*, M=*Medium*, H=*High*, VH=*Very High*, P=*Perfect*$\}$.

In any linguistic model we also need some management operators for linguistic information. An advantage of the ordinal fuzzy linguistic modeling is the simplicity and speed of its computational model. It is based on the symbolic computational model [15] and acts by direct computation on labels by taking into account the order of such linguistic assessments in the ordered structure of labels. Usually, the ordinal fuzzy linguistic model for computing with words is defined by establishing i) a negation operator, ii) comparison operators based on the ordered structure of linguistic terms, and iii) adequate aggregation operators of ordinal fuzzy linguistic information. In most ordinal fuzzy linguistic approaches the negation operator is defined from the semantics associated to the linguistic terms as

$$NEG(s_i) = s_j \mid j = (g - i)$$

and there are defined two comparison operators of linguistic terms:

1. *Maximization operator:* $MAX(s_i, s_j) = s_i$ if $s_i \geq s_j$; and
2. *Minimization operator:* $MIN(s_i, s_j) = s_i$ if $s_i \leq s_j$.

Using these operators it is possible to define automatic and symbolic aggregation operators of linguistic information, as for example the LOWA operator [18]:

Definition 1. Let $A = \{a_1, \ldots, a_m\}$ be a set of labels to be aggregated, then the LOWA operator, ϕ, is defined as:

$$\phi(a_1,\ldots,a_m) = W \cdot B^T = \mathscr{C}^m\{w_k, b_k, k = 1,\ldots,m\}$$
$$= w_1 \odot b_1 \oplus (1-w_1) \odot \mathscr{C}^{m-1}\{\beta_h, b_h, h = 2,\ldots,m\},$$

where $W = [w_1,\ldots,w_m]$ is a weighting vector, such that, $w_i \in [0,1]$ and $\Sigma_i w_i = 1$. $\beta_h = w_h/\Sigma_2^m w_k$, and $B = \{b_1,\ldots,b_m\}$ is a vector associated to A, such that, $B = \sigma(A) = \{a_{\sigma(1)},\ldots,a_{\sigma(m)}\}$, where, $a_{\sigma(j)} \leq a_{\sigma(i)}\ \forall\ i \leq j$, with σ being a permutation over the set of labels A. $\mathscr{C}^m$ is the convex combination operator of m labels and if $m = 2$, then it is defined as:

$$\mathscr{C}^2\{w_i, b_i, i = 1,2\} = w_1 \odot s_j \oplus (1-w_1) \odot s_i = s_k,$$

such that, $k = \min\{g, i + round(w_1 \cdot (j-i))\}$, $s_j,\ s_i \in S$, $(j \geq i)$, where *"round"* is the usual round operation, and $b_1 = s_j$, $b_2 = s_i$. If $w_j = 1$ and $w_i = 0$, with $i \neq j\ \forall i$, then the convex combination is defined as: $\mathscr{C}^m\{w_i, b_i, i = 1,\ldots,m\} = b_j$.

An important question of the LOWA operator is the determination of the weighting vector W. In [48], it was defined an expression to obtain W that allows to represent the concept of fuzzy majority [26] by means of a fuzzy linguistic nondecreasing quantifier Q:

$$w_i = Q(i/n) - Q((i-1)/n),\ i = 1,\ldots,n.$$

When a fuzzy linguistic quantifier Q is used to compute the weights of LOWA operator ϕ, it is symbolized by ϕ_Q.

2.3 Mobile Technologies Usage in GDM Problems

During the last decade, organizations have moved from face-to-face group environments to virtual group environments using communication technology. More and more workers use mobile devices to coordinate and share information with other people. The main objective is that the members of the group could work in an ideal way where they are, having all the necessary information to take the right decisions [25, 31, 43, 44].

To support the new generation of decision makers and to add real-time process in the GDM problem field, many authors have proposed to develop decision support systems based on mobile technologies [9, 41]. Similarly, we propose to incorporate mobile technologies in a DSS obtaining a Mobile DSS (MDSS). Using such a technology should enable a user to maximize the advantages and minimize the drawbacks of DSSs.

The need of a face-to-face meeting disappears with the use of this model because the computer system acts as moderator and experts can communicate with the system directly using their mobile device from any place in the world and at any time. Hereby, a continuous information flow among the system and each member of the group is produced, which can help to reach the consensus between the experts in a faster way and to obtain better decisions.

In addition, MDSS can help to reduce the time constraint in the decision process. Thus, the time saved by using the MDSS can be used to do an exhaustive analysis of the problem and obtain a better problem definition. This time also could be used to identify more feasible alternative solutions to the problem, and thus, the evaluation of a large set of alternatives would increase the possibility of finding a better solution. The MDSS helps to the resolution of GDM problems providing a propitious environment for the communication, increasing the satisfaction of the user and, in this way, improving the final decisions [38].

3 A New Mobile Decision Support System

In this section, we present the implemented prototype to deal with dynamic decision making situations, explaining the architecture and the work flow that summarizes the functions of this system. We show how the consensual and selection processes are controlled.

A DSS can be built in several ways, and the used technology determines how a DSS has to be developed [11, 36]. The most used architecture for mobile devices is the "Client/Server" architecture, where the client is a mobile device. The client/server paradigm is founded on the concept that clients (such as personal computers, or mobile devices) and servers (computers) are both connected by a network enabling servers to provide different services for the clients. When a client sends a request to a server, this server processes the request and sends a response back to client.

We have chosen a *thick-client* model for our implementation. This allows us to use the software in all the mobile devices without taking into account the kind of browser. Furthermore, the technologies that we have used to implement the prototype comprise Java and Java Midlets for the client software, PHP for the server functions and MySQL for the database management.

So, the prototype allows user to send his/her preferences by means of a mobile device, and the system returns to the experts the final solution or recommendations to increase the consensus levels, depending on the status of the decision process. An important aspect is that the user-system interaction can be done anytime and anywhere which facilitates expert's participation and the resolution of the decision process. In what follows, we describe the client and server of the prototype in detail.

3.1 Client Side

The client software shows the next seven interfaces to the experts:

- *Authentication:* The device asks a user and a password to access the system.
- *Connection:* The device must be connected to the network to send/receive information to the server.
- *Problem description:* When a decision process is started, the device shows to the experts a brief description of the problem and the set of alternatives.

- *Insertion of preferences:* The device will have a specific interface to insert the linguistic preferences using a set of labels. To introduce or change the preferences using the interface, the user has to use the keys of the device.
- *Swap of Alternatives:* When a new alternative appears in the environment of the problem because some dynamic external factors have changed and this alternative deserves to be a member of the discussion subset or when an alternative have a low dominance degree to the current temporary solution of consensus, the system asks the experts if they want to modify the discussion subset by swapping these alternatives. The experts can assess if they agree to swap the alternatives sending their answer to the question received. The user can select the chosen degree by using the cursor keys of the device.
- *Feedback:* When opinions should be modified, the device shows experts the recommendations and allows experts to send their new preferences.
- *Output:* At the end of the decision process, the device will show the set of solution alternatives as an ordered set of alternatives.

On the technical side of the development of the client part, it is worth noting that the client application complies with the MIDP 2.0 specifications [1] and that the J2ME Wireless Toolkit 2.2 [2] provided by SUN was used in the development phase. This wireless toolkit is a set of tools that provide J2ME developers with some emulation environments, documentation, and examples to develop MIDP-compliant applications. The application was later tested using a JAVA-enabled mobile phone on a GSM network using a GPRS-enabled SIM card. The MIDP application is packaged inside a JAVA archive (JAR) file, which contains the applications classes and resource files. This JAR file is the one that actually is downloaded to the physical device (mobile phone) along with the JAVA application descriptor file when an expert wants to use our prototype.

3.2 Server Side

The server is the main side of the prototype. It implements the main modules and the database that stores the problem data as well as problem parameters and the information generated during the decision process. The communication with the client to receive/send information from/to the experts is supported by mobile Internet (M-Internet) technologies (see Figure 2). Concretely, the three modules of the server are:

3.2.1 Decision Module

In a GDM problem the experts can present their opinions using different types of preference representation (preference orderings, utility functions or preference relations) [6, 47, 46], but in this contribution, we assume that the experts give their preferences using fuzzy linguistic preference relations.

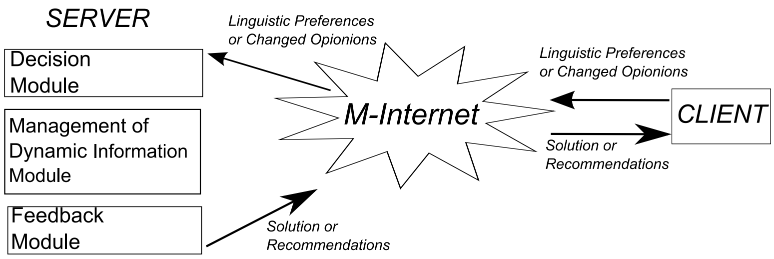


Fig. 2 *Server modules*

Definition 2. A Fuzzy linguistic Preference Relation (FLPR) P^i given by an expert e_i is a fuzzy set defined on the product set $X \times X$, that is characterized by a linguistic membership function

$$\mu_{P^i} : X \times X \longrightarrow S$$

where the value $\mu_{P^i}(x_l, x_k) = p^i_{lk}$ is interpreted as the linguistic preference degree of the alternative x_l over x_k for the expert e_i.

Once experts have sent their preferences, the server starts the decision module to obtain a temporary solution of the problem. In this module the consensus measures are also calculated. This module has two different processes: 1) *selection process* and 2) *consensus process*.

1. *Selection Process:* This process has two different phases [17]:

   a. Aggregation phase:
   This phase defines a collective preference relation, $P^c = (p^c_{lk})$, obtained by means of the aggregation of all individual linguistic preference relations $\{P^1, P^2, \ldots, P^m\}$. It indicates the global preference between every pair of alternatives according to the majority of experts' opinions. The aggregation is carried out by means of a LOWA operator ϕ_Q guided by a fuzzy linguistic non-decreasing quantifier Q [18]:

   $$p^c_{lk} = \phi_Q(p^1_{lk}, \ldots, p^m_{lk})$$

   b. Exploitation phase:
   This phase transforms the global information about the alternatives into a global ranking of them, from which the set of solution alternatives is obtained. The global ranking is obtained applying these two choice degrees of alternatives on the collective preference relation [14]:

   - $QGDD_l$: This quantifier guided dominance degree quantifies the dominance that one alternative x_l has over all the others in a fuzzy majority sense:

   $$QGDD_l = \phi_Q(p^c_{l1}, p^c_{l2}, \ldots, p^c_{l(l-1)}, p^c_{l(l+1)}, \ldots, p^c_{ln})$$

This measure allows us to define the set of non-dominated alternatives with maximum linguistic dominance degree:

$$X^{QGDD} = \{x_l \in X \mid QGDD_l = sup_{x_k \in X} QGDD_k\}$$

- $QGNDD_l$: This quantifier guided non-dominance degree gives the degree in which each alternative x_l is not dominated by a fuzzy majority of the remaining alternatives:

$$QGNDD_l = \phi_Q(NEG(p^s_{1l}), NEG(p^s_{2l}), \ldots,$$

$$NEG(p^s_{(l-1)l}), NEG(p^s_{(l+1)l}), \ldots, NEG(p^s_{nl}))$$

where

$$p^s_{lk} = \begin{cases} s_0 & \text{if } p^c_{lk} < p^c_{kl} \\ s_{I(p^c_{lk})-I(p^c_{kl})} & \text{if } p^c_{lk} \geq p^c_{kl} \end{cases}$$

being $I : S \rightarrow \{0, \ldots, g\} \mid I(s_p) = p \; \forall s_p \in S$.
represents the degree in which x_l is strictly dominated by x_k. The set of of non-dominated alternatives with maximum linguistic non-dominance degree is

$$X^{QGNDD} = \{x_l \in X \mid QGNDD_l = sup_{x_k \in X} QGNDD_k\}$$

2. *Consensus Process:*
We assume that the consensus is a measurable parameter whose highest value corresponds to unanimity and lowest one to complete disagreement. We use some consensus degrees to measure the current level of consensus in the decision process. They are given at three different levels [19, 20, 35]: pairs of alternatives, alternatives and relations. The computation of the consensus degrees is carried out as follows:

   a. For each pair of experts, e_i, e_j $(i < j)$, a similarity matrix, $SM^{ij} = (sm^{ij}_{lk})$, is defined where
   $$sm^{ij}_{lk} = 1 - \frac{|I(p^i_{lk}) - I(p^j_{lk})|}{g}.$$
   b. A consensus matrix, CM, is calculated by aggregating all the similarity matrices using the arithmetic mean as the aggregation function $\bar{x}$:
   $$cm_{lk} = \bar{x}(sm^{ij}_{lk};\ i = 1, ..., m-1,\ j = i+1, ..., m).$$
   c. Once the consensus matrix, CM, is computed, we proceed to calculate the consensus degrees:
      i. *Consensus degree on pairs of alternatives, cp_{lk}*. It measures the agreement on the pair of alternatives (x_l, x_k) amongst all the experts.
      $$cp_{lk} = cm_{lk}.$$

ii. *Consensus degree on alternatives, ca_l*. It measures the agreement on an alternative x_l amongst all the experts.

$$ca_l = \frac{\sum_{k=1}^{n} cp_{lk}}{n}.$$

iii. *Consensus degree on the relation, cr*. It measures the global consensus degree amongst the experts' opinions.

$$cr = \frac{\sum_{l=1}^{n} ca_l}{n}.$$

Initially, in this consensus model we consider that in any nontrivial GDM problem the experts disagree in their opinions so that decision making has to be viewed as an iterative process. This means that agreement is obtained only after some rounds of consultation. In each round, we calculate the consensus measures and check the current agreement existing among experts using cr.

3.2.2 Management of Dynamic Information Module

Classical GDM models are defined in static frameworks. In order to make the decision making process more realistic, this module is able to deal with dynamic parameters in decision making. The main parameter that could vary through the decision making process is the set of alternatives of the problem because it could depend on dynamical external factors like the traffic [8, 32], or the meteorological conditions [7], and so on. In such a way, we can solve dynamic decision problems in which, at every stage of the process, the discussion is centered on different alternatives.

This tool allows to introduce new alternatives in the discussion subset, but this change has to be approved by the experts. To do so, the mechanism has two phases. At the first one, the system identifies the new alternative to include in the set of discussion alternatives (discussion subset) and the worst alternative of the current discussion subset. The second one is to ask experts about if they agree with the replacement and updating the discussion subset [38].

3.2.3 Feedback Module

To guide the change of the experts' opinions, the DSS simulates a group discussion session in which a feedback mechanism is applied to quickly obtain a high consensus level. This mechanism is able to substitute the moderator's actions in the consensus reaching process. The main problem for the feedback mechanism is how to find a way of making individual positions converge and, therefore, how to support the experts in obtaining and agreeing with a particular solution [22]. To do that, we compute others additional consensus measures, called proximity measures [19].

These measures evaluate the agreement between the individual experts' opinions and the group opinion. To compute them for each expert, we need to use the collective FLPR, $P^c = (p^c_{lk})$, calculated previously.

1. For each expert, e_i, a proximity matrix, $PM^i = (pm^i_{lk})$, is obtained where

$$pm^i_{lk} = 1 - \frac{|I(p^i_{lk}) - I(p^c_{lk})|}{g}.$$

2. Computation of proximity measures at three different levels:

   a. *Proximity measure on pairs of alternatives, pp^i_{lk}.* It measures the proximity between the preferences on each pair of alternatives of the expert e_i and the group.

   $$pp^i_{lk} = pm^i_{lk}.$$

   b. *Proximity measure on alternatives, pa^i_l.* It measures the proximity between the preferences on each alternative x_l of the expert e_i and the group.

   $$pa^i_l = \frac{\sum_{k=1}^n pp^i_{lk}}{n}.$$

   c. *Proximity measure on the relation, pr^i.* It measures the global proximity between the preferences of each expert e_i and the group.

   $$pr^i = \frac{\sum_{l=1}^n pa^i_l}{n}.$$

These measures allow us to build a feedback mechanism so that experts change their opinions and narrow their positions [21, 35]. In section 4, we show the use of the mechanism in a practical case of use.

3.3 Communication and Work Flow of the Prototype

Between client and server some communication functions are developed. In what follows, we present how the modules are connected together with the database, and the order in which each of them is executed.

0. **Initialization:** An initial step is to insert in the database all the initial parameters of the linguistic GDM problem.
1. **Verify user messages and store the main information:** When an expert wants to access the system, he has to send a message through M-Internet using his/her mobile device. The user can send two kinds of messages:
   i) A preferences message: It is composed by authentication information (login and password) and his/her preferences about the problem, using a set of labels to represent a FLPR.
   ii) A change of alternatives message: It is composed by authentication information (login and password) and his/her linguistic level of agreement with the proposed change of alternatives.
   These messages are verified by the server, checking the login and password in the database. If the authentication process is correct, the rest of the information

of the message is stored in the database and the server decides if the consensus stage should start (if all experts have provided their preferences) or, if the managing module of dynamic information can be finished (if enough experts provide their agreement degrees on the proposed change of alternatives).

2. **Calculate the set of solution alternatives and the consensus measures:** The decision module returns the solution set of alternatives in each stage of the decision process. All the information about the temporary solution is saved in the database.
3. **Control the consensus state:** In this step, the server determines if the required agreement degree has been reached (and thus, the decision process can be finished) or if we must begin a new round of consensus using the feedback mechanism that generates recommendations to change the experts' preferences.
4. **Management of new alternatives:** When the minimum consensus level has not been reached, the system checks if some new good alternatives appear in the problem environment or an old alternative deserves to be removed.
5. **Generate the recommendations:** In this step, the server calculates the proximity measures and generates the recommendations to change the FLPRs. It sends a message to the experts advising that they can use the software again for reading the recommendations and in such a way to start a new consensus stage. In order to avoid that the collective solution does not converge after several discussion rounds, the prototype stops if the number of rounds surpass MAXCYCLES. These recommendations are saved in the database and sent to the experts through M-Internet.

In the following section we present a practical example on the use of the prototype to provide more detail about its operation.

4 Case of Use: Medical Diagnosis

Medical diagnosis is a GDM scenario that presents all the characteristics to take the advantages of our system. There is a patient who presents some symptoms, but all of them are common to several diseases. These diseases shape the set of alternatives of the problem. In addition, there are some doctors considered specialists in differential diagnosis. They form the set of experts of the problem and they have to jointly diagnose which is the disease that the patient has contracted. The experts work in different hospitals of different countries and they can not have a meeting to discuss and reach the consensual solution. Moreover, this environment is dynamic in the sense that the patient is now moved to the hospital and, at any moment, he could present new symptoms or he could set better due to the medication, and thus, any change of state of the patient might be taken into account by the doctors. So, the experts might decide to use our system because they can use the mobile communication technologies to reach the consensus, and they can change some possible diseases in the discussion set of alternatives according with the current patient's state.

The first step to solve a problem using our prototype is to insert all the initial parameters of the problem (experts, alternatives, thresholds, timing...) in the database. We assume a set of three experts (doctors), $\{e_1, e_2, e_3\}$, and a set of four alternatives (possible diseases) $\{x_1 = Cold,\ x_2 = Swine\ Flu,\ x_3 = Cancer,\ x_4 = Lupus\}$. The remaining parameters (see table 1) are used by the system to obtain the necessary consensus degree among the experts.

Table 1 Initial parameters of the problem

Name	*Value*	*Description*
Ndiseases	4	Number of diseases in the discussion subset
Nexperts	3	Number of experts (doctors)
minConsDegree	0.75	Minimum consensus level required by the problem
minProxDegree	0.75	Minimum proximity level required for the experts to be noted to change
MAXCYCLES	4	Maximum number of iterations of the consensus process
maxTime	12 (hours)	Maximum time of waiting for the experts opinions to change
minQGDD	L	Minimum dominance level that an alternative has to reach to avoid to be changed

When the initial parameters of the problem are defined, the decision making process starts.

4.1 First Round

The three experts send their FLPRs using their mobile devices and the following set of seven labels (see Figure 3): $S = \{s_0 = N, s_1 = VL, s_2 = L, s_3 = M, s_4 = H, s_5 = VH, s_6 = P\}$, where N=*Null*, VL=*Very Low*, L=*Low*, M=*Medium*, H=*High*, VH=*Very High* and P=*Perfect*.

(a) Expert 1 (b) Expert 2 (c) Expert 3

Fig. 3 Expert Preferences

4.1.1 Decision Module

1. Selection Process:

In this phase we obtain the collective temporary solution by aggregating the experts' preferences.

1. Aggregation:
   We aggregate he FPLRs by means of the LOWA operator. We use the linguistic quantifier *most of* defined as $Q(r) = r^{1/2}$. Then, we obtain the following collective FLPR:

$$P^c = \begin{pmatrix} - & L & H & M \\ VH & - & H & VH \\ H & M & - & M \\ M & M & H & - \end{pmatrix}$$

2. Exploitation:
   Using again the same linguistic quantifier *most of*, we obtain $QGDD_i$ and $QGNDD_i\ \forall x_i \in X$:

Table 2 Choice degrees

	x_1	x_2	x_3	x_4
$QGDD_i$	M	VH	H	H
$QGNDD_i$	VH	P	P	P

and, the maximal sets are:

$$X^{QGDD} = \{x_2\} \text{ and } X^{QGNDD} = \{x_2, x_3, x_4\}.$$

2. Consensus Process:

In this phase the system calculates the consensus measures.

1. *Similarity matrices:*

$$SM_{12} = \begin{pmatrix} - & 0.83 & 0.66 & 0.66 \\ 0.50 & - & 0.50 & 0.16 \\ 0.50 & 0.66 & - & 0.83 \\ 0.16 & 0.66 & 0.66 & - \end{pmatrix}$$

$$SM_{13} = \begin{pmatrix} - & 0.66 & 0.66 & 0.83 \\ 0.83 & - & 0.33 & 0.50 \\ 0.50 & 0.33 & - & 0.83 \\ 0.50 & 0.50 & 0.83 & - \end{pmatrix}$$

$$SM_{23} = \begin{pmatrix} - & 0.83 & 1.00 & 0.83 \\ 0.66 & - & 0.83 & 0.66 \\ 1.00 & 0.66 & - & 1.00 \\ 0.66 & 0.83 & 0.83 & - \end{pmatrix}$$

2. *Consensus matrix:*

$$CM = \begin{pmatrix} - & 0.77 & 0.77 & 0.77 \\ 0.66 & - & 0.55 & 0.44 \\ 0.66 & 0.55 & - & 0.88 \\ 0.44 & 0.66 & 0.77 & - \end{pmatrix}$$

3. *Consensus degrees on pairs of alternatives.* The element (l,k) of CM represents the consensus degrees on the pair of alternatives (x_l, x_k).
4. *Consensus on alternatives:*

$$ca^1 = 0.77 \quad ca^2 = 0.55 \quad ca^3 = 0.69 \quad ca^4 = 0.62$$

5. *Consensus on the relation:*

$$cr = 0.66$$

As $cr < minConsDegree = 0.75$ is satisfied, then it is concluded that there is no consensus amongst the experts, and consequently, the system should continue by executing the next two processes: managing process of dynamic information to replace some alternatives in the discussion subset and feedback process to support the experts' changes in their preferences in order to increase cr.

4.1.2 Management of Dynamic Information Module

As soon as the system has verified that the minimum consensus level among the experts has not been reached and before beginning a new round of consensus, it is necessary to update all the information of the problem that could be changed during the process.

In this case, the patient, due to the medication, has started to show a new symptom that is typical of a disease that was not included in the initial discussion subset of the problem and should be included now ($x_5 = Allergy$). This new situation does not pose any problem because the system manages the dynamic information. We identify those alternatives with low choice degrees ($x_1 = Cold$) and ask the experts if they agree to replace those identified alternatives by the new suitable alternative (See Figure 4a).

The experts' answers were the following: *(Agree, Nor Agree/Nor Disagree and Completely Agree)*. The system applies the LOWA operator to aggregate these opinions and obtain a collective agreement degree. In this case we obtain ,(Agree), what represents an affirmative position to introduce the changes of alternatives. Therefore, the change of *Cold* by *Allergy* is done. The experts will be informed about it and then they are urged to refill their preferences by considering in this occasion the new alternative.

4.1.3 Feedback Module

- **Computation of proximity measures:**

1. *Proximity matrices:*

$$PM_1 = \begin{pmatrix} - & 0.83 & 0.66 & 0.83 \\ 0.66 & - & 0.50 & 0.33 \\ 0.83 & 0.83 & - & 1.00 \\ 0.66 & 0.83 & 0.83 & - \end{pmatrix}$$

$$PM_2 = \begin{pmatrix} - & 1.00 & 1.00 & 0.83 \\ 0.83 & - & 1.00 & 0.83 \\ 0.66 & 0.83 & - & 0.83 \\ 0.50 & 0.83 & 0.83 & - \end{pmatrix}$$

$$PM_3 = \begin{pmatrix} - & 0.83 & 1.00 & 1.00 \\ 0.83 & - & 0.83 & 0.83 \\ 0.66 & 0.50 & - & 0.83 \\ 0.83 & 0.66 & 1.00 & - \end{pmatrix}$$

2. *Proximity on pairs of alternatives:* $PP_i = PM_i$.
3. *Proximity on alternatives (See Table 3):*

Table 3 Proximity measures on alternatives

x_1	x_2	x_3	x_4
$pa_1^1 = 0.77$	$pa_1^2 = 0.50$	$pa_1^3 = 0.88$	$pa_1^4 = 0.77$
$pa_2^1 = 0.94$	$pa_2^2 = 0.88$	$pa_2^3 = 0.77$	$pa_2^4 = 0.72$
$pa_3^1 = 0.94$	$pa_3^2 = 0.83$	$pa_3^3 = 0.66$	$pa_3^4 = 0.83$

4. *Proximity on the relation:*

$$pr_1 = 0.73 \quad pr_2 = 0.83 \quad pr_3 = 0.81$$

- **Production of advice:**

1. *Identification phase:*
   a. Identification of experts:

$$EXPCH = \{e_i \mid pr_i < minProxDegree\} = \{e_1\}$$

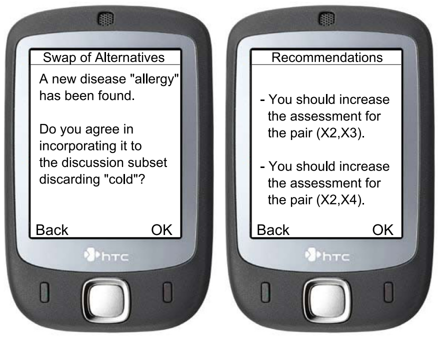
   b. Identification of alternatives:

$$ALT_1 = \{x_l \in X \mid pa_l^i < minProxDegree \wedge e_i \in EXPCH\} = \{x_2\}$$

   c. Identification of pairs of alternatives to generate recomendations:

$$PALT_1 = \{(x_2, x_1), (x_2, x_3), (x_2, x_4)\}$$

2. *Recommendation phase:*
In this phase, we have to take into account that alternative x_1 has been replaced in the previous process by x_5. So, x_1 does not need rules to be modified and there is a new alternative in the discussion subset, x_5, that needs new preference values. The recommendations interface for the expert e_1 is shown in Figure 4b.
   a. Rules to change the opinions:
      – Because x_1 has been replaced, p^1_{21} does not need to be modified.
      – Because $p^1_{23} < p^c_{23}$, expert e_1 is advised to increase the assessment of this preference value.
      – Because $p^1_{24} < p^c_{24}$, expert e_1 is advised to increase the assessment of this preference value.



(a) Swap of alternatives (b) Recommendations

Fig. 4

4.2 Second Round

The experts send their preferences about the new discussion subset to start the second round (see Figure 5).

(a) Expert 1 (b) Expert 2 (c) Expert 3

Fig. 5 Expert Preferences

4.2.1 Decision Module

1. Selection Process:

1. Aggregation:
   The collective FLPR is:

$$P^c = \begin{pmatrix} - & VH & H & H \\ L & - & H & VH \\ M & M & - & M \\ M & M & H & - \end{pmatrix}$$

2. Exploitation:
   Using again the same linguistic quantifier "most of", we obtain the following choice degrees:

Table 4 Choice degrees in 2nd round

	x_5	x_2	x_3	x_4
$QGDD_i$	VH	H	M	H
$QGNDD_i$	P	VH	VH	VH

Clearly, the maximal sets are:

$$X^{QGDD} = \{x_5\} \text{ and } X^{QGNDD} = \{x_5\}.$$

2. Consensus Process:

Consensus on the relation:

$$cr = 0.79$$

Because $cr > minConsDegree$, then it is concluded that there is the required consensus amongst the experts, and consequently, the current solution is the final solution, that is stored and sent to the experts (see Figure 6).

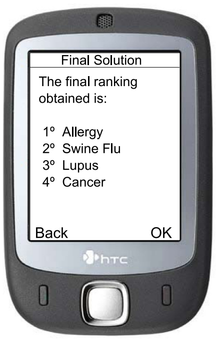


Fig. 6 Final solution

According to these results, doctors agree that the most suitable disease, taking into account all the dynamic symptoms, is allergy. In such a way, the patient can receive the most appropriate treatment.

5 Conclusions

We have presented a new prototype of DSS based on dynamic information and mobile technologies which provides consensual and selection support to deal with dynamic decision making situations. There are a large number of scenarios in which the deployment of DSSs on mobile devices is desirable. So, it is specifically designed to deal with GDM problems based on dynamic sets of alternatives, which uses the advantages of mobile Internet technologies to improve the user-system interaction through decision process. In this prototype we allow the experts to use linguistic preference relations to express their preferences. In short, with this new mobile decision support system we shall be able to deal with linguistic GDM problems in which experts could interact anywhere and anytime, quickly, in a flexible way and under dynamic frameworks.

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