

Arguing with Behavior Influence: A Model for Web-Based Group Decision Support Systems

João Carneiro*

*GECAD — Research Group on Intelligent Engineering
and Computing for Advanced Innovation and Development
Institute of Engineering — Polytechnic of Porto, Portugal*

*ALGORITMI Centre, Informatics Department — University of Minho
Guimarães, Portugal
joaomrcarneiro@gmail.com*

Diogo Martinho and Goreti Marreiros

*GECAD — Research Group on Intelligent Engineering
and Computing for Advanced Innovation and Development
Institute of Engineering — Polytechnic of Porto, Portugal*

Paulo Novais

*ALGORITMI Centre, Informatics Department — University of Minho
Guimarães, Portugal*

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In this work, we propose an argumentation-based dialogue model designed for Web-based Group Decision Support Systems, that considers the decision-makers' intentions. The intentions are modeled as behavior styles which allow agents to interact with each other as humans would in face-to-face meetings. In addition, we propose a set of arguments that can be used by the agents to perform and evaluate requests, while considering the agents' behavior style. The inclusion of decision-makers' intentions intends to create a more reliable and realistic process. Our model proved, in different contexts, that higher levels of consensus and satisfaction are achieved when using agents modeled with behavior styles compared to agents without any features to represent the decision-makers' intentions.

Keywords: Web-based group decision support systems; argumentation; multi-agent systems; decision-making; multi-criteria problems; cognitive aspects.

1. Introduction

It is known that many of the decisions taken in organizations are made in groups.¹ Group decision-making is a process in which a group of people, called participants,

*Corresponding author.

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act collectively to analyze a set of variables, considering and evaluating the available alternatives, selecting one or more solutions for a certain problem. The number of participants involved in the process is variable and all of them may be either at the same place and at the same time or geographically dispersed at different times.² There are two main reasons for which decisions are made in groups: on the one hand, most of the current organizations organigrams involve several decision-makers,² both at the strategic³ and at the technical level,⁴ on the other hand, group decisions can potentiate the decision quality.^{5–7} Group Decision Support Systems (GDSS) have been widely studied throughout the last decades to support this type of decisions.^{8–11} However, in the last 10/20 years, we have seen a remarkable change in the context where the decision-making process happens, especially in large organizations.^{12–14} With the emergence of global markets, the growth of multinational organizations and a more globalist view of the planet, we can easily find decision-makers (chief executive officers, managers and other members of global virtual teams) spread around the world, in countries with different time zones.¹⁵ Moreover, it is especially complex to support the group decision-making process in this context, due to the decision-makers being geographically dispersed. This can lead to additional problems: failure to communicate and retain contextual information, unevenly distributed information, difficulty to communicate and to understand the salience of information, differences in the speed of access to information, and difficulty to interpret the meaning of silence¹⁶; and to deal with temporal issues, which can originate: ambiguity, conflicting temporal interests and constraints, and scarcity of temporal resources.¹⁷ To provide an answer and operate correctly in this type of scenarios, the traditional GDSS have evolved to what is known as Ubiquitous/Web-based Group Decision Support Systems (Web-based GDSS).^{18–20} The idea behind the Web-based GDSS is to support the group decision-making process “anytime” and “anywhere”, and help deal with some of the referred problems.^{21,22}

In a group decision-making process, there is a conflict of interests and each party involved may (or may not) have different objectives and needs that intends to satisfy and pursuit.²³ Some strategies that can be used in Web-based GDSS have been proposed over the years such as Multiple-Criteria Decision Analysis (MCDA)^{24–27} methods and automatic negotiation models (game theory, heuristics and argumentation).^{28–30} These strategies intend to help decision-makers in achieving an agreement through frameworks and other specific strategies.^{31–33} During a real face-to-face decision-making process, dialogues can assume different types like: persuasion, information-seeking, inquiry, among others.³⁴ The argumentation-based dialogue models can be a suitable strategy to help overcome the lack of interaction inherent to the decision-making processes in which decision-makers are geographically dispersed.^{29,35,36} They allow agents (that represent decision-makers) to exchange proposals, including justifications and explanations, which are essential for an agent to negotiate with other agents.³⁷ Furthermore, the arguments can be used to inform decision-makers about the reasons why agents propose a certain solution.³⁸ The most striking approaches were proposed about two decades ago.^{39–41} Since then, we

have seen different (extensions) approaches to formulate argumentation frameworks, such as: abstract argumentation,^{42,43} logic-based argumentation,^{44,45} value-based argumentation,^{46,47} assumption-based argumentation,^{48,49} among others.⁵⁰ However, these approaches deal with argumentation as a somewhat one-sided-process “in which a single party merely presents a reasoned justification”.⁵¹ In the context of group decision-support, the paradigm is different, the argumentation is “an informed exchange of ideas and positions involving several contributors: in other words, argumentation concerning an issue”, which typically, arises as a dialogical process.⁵¹ Some strategies have been proposed to deal with dialogical processes,^{52–54} most of which are oriented to multi-agent systems and formalize some typical aspects, such as: locutions, utterances, rules for dialogue continuation and termination. However, when we search for argumentation-based dialogue models specifically adapted to GDSS, the results are almost inexistent. The few existing results are outdated^{36,55} and even if some seemed promising in the way they could be adapted to this area,^{40,41} the works that came next followed (most of the times) another path (despite some of them remain within decision support).

The benefits inherent to group decision-making must not be overlooked when developing Web-based GDSS. A typical face-to-face meeting allows decision-makers to interact, exchange ideas and work on and generate new knowledge and intelligence.^{5–7} As we had seen, (in an ideal scenario) we can achieve some of these benefits using automatic negotiation models (for instance: argumentation-based dialogue models). However, more factors should be considered besides the “messages” exchanged by decision-makers to correctly represent decision-makers. This representation can range from criteria’s evaluation (for instance in a multi-criteria problem⁵⁶ to a complete representation of the individual (for instance: personality, emotions and mood.^{57–59} The face-to-face meetings benefit from the decision-makers’ heterogeneity⁶⁰ as it is related to the decision-makers’ temperament but also with the decision-makers’ intentions. Let us consider a scenario where a group of friends intends to choose a restaurant to celebrate the anniversary of one of them. Obviously, as in any other multi-criteria problem, each person would have his own preferences concerning each of the possible alternatives. However, how important would be the consideration of each element’s intentions? Is it possible that some just want to please the birthday person? If so, should not they be more willing to accept that person preferences? What would happen if they used a Web-based GDSS which only considered the preferences of participants (towards alternatives and criteria) and ignored their intentions? Would the group satisfaction resulting from the decision made be the expected? In order to answer these questions, it is necessary to allow decision-makers to configure not only their preferences (on alternatives and criteria), but also their intentions and other aspects that may be relevant, so that their position can be expressed with the best possible representation.

Modeling agents with human-like is not a novelty. In fact, at the start of the new millennium, some projects dealing with agents’ humanization began to appear.⁶¹ Nowadays, there are many proposals that intend to model human characteristics in

agents, such as: personality,^{62,63} emotions,^{57,64} cognitive styles,⁶⁵ among others.^{66–68} There are also some proposals targeted towards GDSS.^{59,69–71} All of them share the idea that including cognitive/affective aspects will contribute in some way to the decision-making process. However, to the best of our knowledge, most of them are envisaged for use in simulated environments. The usage of such techniques in real systems can bring some disadvantages. For example, “a real me” can be a bad approach if my persona is less persuasive/intelligent/capable than others. No one will be interested in using an application that depreciates you. Moreover, including aspects such as personality does not allow to reflect other aspects such as intentions and objectives. For each decision-maker, the objectives and intentions can vary even for the same problem. In the previous example (to select a restaurant to celebrate the birthday of one of the group members), we could use the decision-makers’ personality to define the interactions between agents and how each agent behaves, however this approach is not enough to identify the intentions of each one of the decision-makers.

In this paper, we propose an argumentation-based dialogue model to support decision-makers in the group decision-making process. In our proposal each agent can assume a style of behavior to represent the intentions of the decision-maker. This behavior is responsible for defining how agents use the argumentation model and how they evaluate received requests. Due to the specific needs inherent to the group decision-making process, our proposal allows agents to be: competitive between them, i.e., allow agents to be capable of pursuing the decision-makers’ preferences; and collaborative, i.e., allow agents to work together to achieve the best outcomes for the group. We intend to prove that the inclusion of styles of behavior is a major asset in this type of context. In addition, we study if by including styles of behavior, the amount of intelligence generated does not decrease (in fact, our goal is to generate more and better intelligence). We also do not want to achieve a fake increase of the consensus level just by including styles of behavior. It is important to know if agents do not neglect their preferences while trying to defend the intentions of the decision-maker. We believe that a correct representation of the decision-makers’ intentions improves the ability to achieve consensus and at the same time improves the decision quality. However, with our proposal, we do not want to force the achievement of consensus, and we want the process to flow naturally, always knowing that sometimes there might not be enough conditions to achieve consensus. We are considering a process with almost no interaction between decision-makers, which means these decision-makers require an iterative process to reason about the problem, to understand other points of view and to reconfigure their preferences. These points are respected in our proposal. Finally, our proposal takes advantage of the benefits associated to the use of multiple agents and the use of group decision-making process through the agents’ capacity to represent the decision-makers’ preferences and intentions.

The rest of the paper is organized in the following order: in the next section, we contextualize the reader through the presentation of our previous approach to deal with styles of behavior in the decision-making process. Our proposal is presented in Sec. 3. In Sec. 4, we deal with the evaluation and results and in Sec. 5 the discussion is

presented. In Sec. 6, we present the related work and finally, some conclusions are taken in Sec. 7, along with the work to be done hereafter.

2. Styles of Behavior for Decision-Making

There are a considerable number of proposals in the literature of computer science related to the agents' humanization. Most of existing proposals have used models such as: Five Factor Model,⁷² OCC⁷³ and PAD.⁷⁴ To develop more intelligent applications, we have seen an increasing of multi-disciplinary works. There are some models in the literature of psychology that define roles/behaviors/designations of individuals. These approaches can be used, adapted or included in simulators or real systems.

In this section, we describe a model previously proposed by us⁷⁵ that intends to allow agents to represent the decision-makers' intentions. A theoretical presentation of this model is essential for a better comprehension of the work proposed in this paper. We consider the decision-makers' intentions as what they: intend (a purpose), plan, desire and/or aspire. Previously, we demonstrated (in the introduction section) that intentions can vary for the same problem in different situations/contexts. To reach the decision-maker's intentions the agent should behave accordingly. We adopted the conflict styles proposed by Rahim and Magner,⁷⁶ and redefined them to be more adequate to the context of group decision-making. We called them styles of behavior and defined them as follows:

- **Dominating:** A dominating individual believes that he owns the key to solve the problem. He plays a very active role during the decision-making process and tries to force his opinions on other participants;
- **Integrating:** An integrating individual favors a collaborative style. He aims to achieve consensual decisions and greatly values his and others' opinions. He prefers to manage assiduously the entire decision-making process;
- **Compromising:** A compromising individual favors a collaborative style. He aims to achieve consensual decisions and values his and others' opinions. He plays a moderately active role during the decision-making process;
- **Obliging:** An obliging individual tends to give up on his opinions in favor of the group interests. He prefers to follow others' opinions rather than sharing his owns;
- **Avoiding:** An avoiding individual prefers to be freed from responsibility. Fundamentally, he prefers to not be involved in the decision-making process and devalues both the process and the opinions of other participants.

Using a correlation between the work proposed by Rahim and Magner⁷⁶ and the facets identified by Costa and MacCrae⁷⁷ we then proposed four dimensions suitable to the context of group decision-making: activity level, resistance to change, concern for self and concern for others. These dimensions represent:

- **Activity level:** High activity levels reflect leadership and vigorousness. Low activity levels reflect leisurely and low need for thrills;

- **Resistance to change:** High resistance to change reflect humble, eager to help and easily moved. Low resistance to change reflect aggressive, superior and skeptical;
- **Concern for self:** High or low interests to satisfy his or her concerns;
- **Concern for others:** High or low interests to satisfy the concerns of others.

The information available in the literature only allows us to define each style of behavior in these dimensions using classifications as low, mid and high. However, to computerize this model and to make agents correctly represent different intentions, we converted these classifications into numerical values. Let us suppose that an existent model considers a dominating behavior as the equivalent of having a low concern for others. How can we know if whenever a decision-maker selects the dominating behavior style to model his agent, he is expecting this “low concern for others”? To deal with these issues, we ran a survey to understand if it was possible to find homogeneous answers to define each style of behavior in each dimension (numerically). The objective was to verify if the behavior styles are perceived in the same way and if that can be converted to a numerical value. The study involved 64 participants, 39 men and 25 women, aged between 19 and 68 years old ($M = 33.56$; $SD = 10.84$) all of which either had higher education degrees or were undergraduate students (10%). In respect to their fields of expertise, respondents were professionals from a wide variety of backgrounds, ranging from technology to social sciences. We asked them to classify the five proposed behavior styles in four dimensions: Concern for self; Concern for others; Resistance to change; and Activity level in a questionnaire with values ranging from 0 to 10 (by means of a visual analogic scale). All respondents were asked to fill out the questionnaire in the researcher’s presence to ensure engagement in the task and/or to aid in the clarification of concepts or modes of signaling the answers. We used the Intraclass Correlation Coefficient to study the agreement level. For all dimensions results were above 0.900 (more precisely between 0.915 and 0.941), with highly significant results ($p < 0.001$). The values obtained in this study helped us to define the actuation levels for each style of behavior in each dimension as can be consulted in Table 1 (the values were normalized to the [0,1] range). This behavior style model plays an important role to understand the work proposed in this paper. An interest finding of this work was that none of the proposed styles of behavior is always more advantageous over others regardless of context.

Table 1. Behavior style measures for each dimension.

Behavior style	Activity level (\bar{X})	Resistance to change (\bar{X})	Concern for self (\bar{X})	Concern for others (\bar{X})
Dominating	0.94	0.92	0.95	0.17
Integrating	0.90	0.54	0.78	0.85
Compromising	0.58	0.42	0.55	0.62
Obliging	0.23	0.12	0.20	0.87
Avoiding	0.05	0.10	0.11	0.09

This is an incentive for decision-makers to choose the style of behavior that better fits their intentions.

3. Methods

In this paper, we consider the following structure of a decision problem: there are a set of possible alternatives A , a set of criteria C , and a set of agents Ag , such that each alternative $a \in A$ has a value for all the defined criteria C . The decision problem has a defined communication language \mathcal{L}_c which allows agents Ag to communicate. To operate with the defined \mathcal{L}_c , there is a set of algorithms \mathcal{L}_a , which specify for each illocution $\varphi \in \mathcal{L}_c$ its effect. The relations between alternatives, criteria, agents, communication language and algorithms jointly form a decision system, represented as follows:

Definition 1. A decision system $(C, A, \text{Ag}, \mathcal{L}_c, \mathcal{L}_a)$, is a five-tuple where:

- a set of criteria $C = \{c_1, c_2, \dots, c_n\}, n > 0$;
- a set of alternatives $A = \{a_1, a_2, \dots, a_m\}, m > 0$;
- a set of agents $\text{Ag} = \{\text{ag}_1, \text{ag}_2, \dots, \text{ag}_k\}, k > 0$;
- a communication language \mathcal{L}_c , consisting of a set of all illocutions;
- a set of algorithms working as regulation \mathcal{L}_a for \mathcal{L}_c , specifying for each locution $\varphi \in \mathcal{L}_c$ its effects.

An agent is a virtual representation of a decision-maker and is defined as follows:

Definition 2. An agent $\text{ag}_i = \{\beta_{\text{ag}_i}, \text{Pr}_{\text{ag}_i}, C_{\text{ag}_i}, A_{\text{ag}_i}, O_{\text{ag}_i}, K_{\text{ag}_i}\}$ is a seven-tuple where:

- $\forall \text{ag}_i \in \text{Ag}, i \in \{1, 2, \dots, n\}$;
- β_{ag_i} is the agent's behavior style (Dominating, Compromising, Obliging, Integrating, Avoiding and No Style);
- Pr_{ag_i} is the agent's protocol for \mathcal{L}_c , specifying the 'legal' moves at each instant t . A protocol on \mathcal{L}_c is a set of illocutions available to ag_i , where $\text{Pr}_{\text{ag}_i} \subseteq \mathcal{L}_c$;
- C_{ag_i} is the agent's evaluation of each criterion, $C_{\text{ag}_i} = \{\text{Ev}_{c_1}, \text{Ev}_{c_2}, \dots, \text{Ev}_{c_n}\}$, $\text{Ev}_{c_j} \in \{[0, 1], \perp\}$;
- A_{ag_i} is the agent's evaluation of each alternative, $A_{\text{ag}_i} = \{\text{Ev}_{a_1}, \text{Ev}_{a_2}, \dots, \text{Ev}_{a_n}\}$, $\text{Ev}_{a_n} \in \{[0, 1], \perp\}$;
- O_{ag_i} is the set of agent's objectives, $O_{\text{ag}_i} \subseteq A \cup C$, preference relation \geq on the set O_{ag_i} ;
- K_{ag_i} is the agent's knowledge, containing the list of all sent and received messages, as well as the preferences of other agents, according to the knowledge he possess in a certain time instant of t .

The agent's objectives (O_{ag_i}) are sorted in a list using the following formula:

$$A_{\text{Result}_{o_i}} = \frac{o_i * \text{CS} + \left(\frac{\text{NS}}{\text{ND}}\right) * \text{CO}}{\text{CS} + \text{CO}}, \quad (1)$$

where:

- o_i is the assessment done to the objective i for which the result is being measured;
- CS is the value of Concern for Self;
- NS is the current number of agents supporting o_i ;
- ND is the total number of participating agents;
- CO is the value of Concern for Others.

Agent's objectives change throughout the decision-making process. This formula relates the concern for self of the behavior style defined by the decision-maker with the evaluation done for each alternative ($o_i * CS$). This way, the agent can measure the “analytical” interests of the decision-maker. Besides this, the formula relates the number of supporters for each alternative with the concern for others of the defined behavior style which will allow the agent to measure the social interests of the decision-maker ($(\frac{NS}{ND}) * CO$).

Definition 3. A behavior $\beta_i = \{Rc_{\beta_i}, Al_{\beta_i}, Cs_{\beta_i}, Co_{\beta_i}\}$ is a four-tuple where:

- Rc_{β_i} is the agent's resistance to change dimension value;
- Al_{β_i} is agent's activity level dimension value;
- Cs_{β_i} is the agent's concern for self dimension value;
- Co_{β_i} is the agent's concern for others dimension value.

A behavior style is represented by the values on each dimension, e.g., Dominating (0.92, 0.94, 0.95, 0.17). In this work, we used the value of each dimension to define the probability for an agent performing an action:

- **Activity level:** probability for an agent to start a dialogue;
- **Resistance to change:** is used to define the acceptance range when an agent receives a request;
- **Concern for self:** is used to order objectives and when the agent decides to perform a “prefer” or a “question” illocution;
- **Concern for others:** is used in the evaluation of requests with the argument appealing to common practices, to order objectives and when the agent decides to perform a “prefer” or a “question” illocution.

Agents communicate by exchanging messages. Figure 1 represents the internal message flow of an agent. Messages exchanged by agents are defined as illocutions. Among other things, an illocution is composed by an utterance and may include (or not) an argument. The agent begins by checking the type of illocution associated to the received message. In the case of a request, it is evaluated and, based on the evaluation, a response is generated indicating whether the request was accepted or rejected. Based on these request-reception and response-formulation events, the agent updates its “Self Preferences Knowledge Base” and finally, sends the response in the format of a message. In case of a Statement or Question illocution, the agent begins by updating its “Opponents' Preferences Knowledge Base” according to the

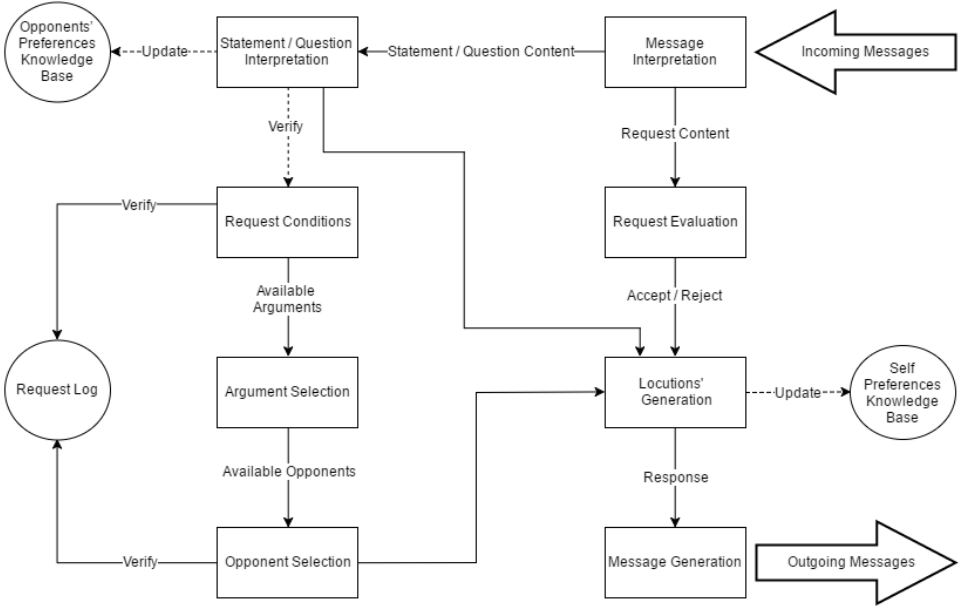


Fig. 1. Agents' communication workflow.

new received knowledge. The agent then performs two actions. The first one, that always and necessarily happens, which is to generate a message to respond to the received message, and the second one which is to verify if, according to that new knowledge, the necessary conditions to make a request are verified. To do so, the agent checks for available arguments as well as opponents to receive those arguments. If these conditions are verified the illocution is generated, and the request message is sent.

An illocution is represented as follows:

Definition 4. An illocution $\psi_i = \{\text{tr}_{\psi_i}, \varphi_{\psi_i}, \alpha_{\psi_i}, \text{Vr}_{\psi_i}, \text{en}_{s_{\psi_i}}, \text{En}_{r_{\psi_i}}\}$ is a six-tuple where:

- $i \in \{1, 2, \dots, n\}$;
- tr_{ψ_i} is the target associated with the illocution (can be null or be another illocution);
- φ_{ψ_i} is the utterance sent in the message;
- α_{ψ_i} is the justification associated to the illocution (can be an argument or can be null);
- Vr_{ψ_i} is the set of variables associated to the illocution (Alternative or Criterion);
- $\text{en}_{s_{\psi_i}}$ is the agent/user who sent the message;
- $\text{En}_{r_{\psi_i}}$ is the set of agents/users who will receive the message (can be 1 or several).

We defined a set of possible illocutions (presented in Table 2). These illocutions represent what agents can dialogue about using a typical multi-criteria problem

Table 2. Considered illocutions.

Illocution	Interpersonal conflict	Utterance	Variables
prefer	CS	“For me the most important criterion/a is/ are 1, 2, . . . , n”	Criterion 1/2/ . . . /n
prefer	CS	“For me the less important criterion/a is/are 1, 2, . . . , n”	Criterion 1/2/ . . . /n
prefer	CS	“My preferred alternative/s is/are 1, 2, . . . , n”	Alternative 1/2/ . . . /n
prefer	CS	“My least preferred alternative/s is/are 1, 2, . . . , n”	Alternative 1/2/ . . . /n
question	CO	“Which criterion/a do you consider most important?”	—
question	CO	“Which criterion/a do you consider less important?”	—
question	CO	“Which alternative/s do you prefer?”	—
question	CO	“Which alternative/s do you prefer to discard?”	—
agree	—	“I agree.”	—
disagree	—	“I disagree.”	—
no-knowledge	—	“I do not have that information.”	—
request	—	“Do you accept the alternative x as the solution?”	Alternative x
request	—	“Can you discard alternative x ?”	Alternative x
accept	—	“I accept.”	Alternative 1/2/ . . . /n
reject	—	“I do not accept.”	Alternative 1/2/ . . . /n

configuration (for instance, using the template proposed in Ref. 56. We considered eight different illocutions (prefer, question, agree, disagree, no-knowledge, request, accept and reject). The “prefer” type of illocutions is used mostly by agents with a higher value of concern for self than the value of concern for others. We assume that agents with a higher concern for self, try to “impose” their preferences to other agents. The “questions” type of illocutions is used mostly by agents with a higher value of concern for others than the value of concern for self. We assume that agents with a higher concern for others are more concerned about other agents’ opinions.

There is an impact associated with starting a dialogue using a “question” or a “prefer” illocution. For example, when an agent says: “My preferred alternative is a_i ”, other agents can answer using four possible illocutions: agree, disagree, question and no-knowledge. This means that at a certain moment in the process those agents will know who is supporting a_i and will not have any knowledge regarding other alternatives. This information has impact in the order of objectives of each agent, affects the selection of arguments to use in requests and affects the evaluation of requests.

Figure 2 is the sequence diagram that represents the proposed negotiation protocol. This diagram is a representation of our technical implementation and was used in the prototype that was developed to run the simulations presented in Sec. 4.

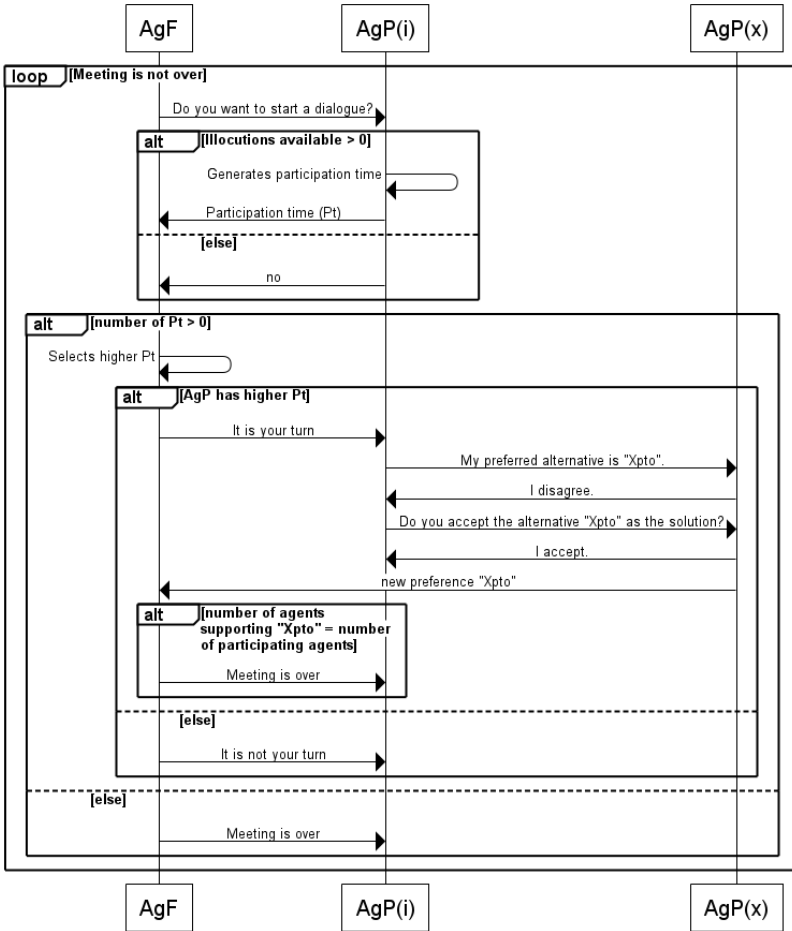


Fig. 2. Agents' interaction workflow.

We created a Facilitator Agent (AgF) to manage the simulated meeting. We have defined two termination rules: when the agents have no more illocutions to exchange between themselves and whenever consensus is reached. When an agent wants to start a dialogue (using a “prefer” or a “question”) he generates a participation time based in his style of behavior. Obviously, the dominating and integrating agents have a higher probability to start a dialogue because they have a higher value for the activity level. The AgF will select the agent with the higher participation time and allow that agent to speak first. All other agents are informed by AgF that they do not have the right to speak. The messages exchanged between AgP(*i*) and AgP(*x*) represent just an example of a dialogue between participating agents. The purpose of this representation is to demonstrate what is happening when an agent adds a new preference. Every time an agent adds a new preference he sends a message to AgF

informing about the new preference. The flow represented between AgF and AgP(*i*) is the same that occurs between AgF and all other participating agents.

3.1. The dialogue moves

It is now presented the set of dialogue moves used in this model. For each move, we define what we call rationality rules, dialogue rules, and action rules. These are based on the rules suggested by Maudet and Evrard.⁷⁸ The rationality rules specify the preconditions for playing the move. The action rules specify the move's implications. The dialogue rules specify the next moves other agents can make, that corresponds to the protocol under which the dialogue takes place.

We start with the dialogical move “prefer”:

$\text{prefer}(\psi_x \vee \text{null}, \varphi_{\psi_i}, \alpha_{\psi_i}, \text{Vr}_{\psi_i}, \text{ag}_{\psi_i}, \text{En}_{r_{\psi_i}})$ is an illocution ψ_i in \mathcal{L}_c .

rationality the agent ag_{ψ_i} intends to declare his opinions about an alternative/s or a criterion/a. He also intends to know if other agents agree/disagree with him and to create a group supporting his preferences.

dialogue $\forall \text{ag}_j \in \text{En}_{r_{\psi_i}}$ can:

$\text{agree}(\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, \text{Vr}_{\psi_k}, \text{ag}_j, \text{En}_{r_{\psi_k}}),$
 $\text{disagree}(\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, \text{Vr}_{\psi_k}, \text{ag}_j, \text{En}_{r_{\psi_k}}),$
 $\text{request}(\text{null}, \varphi_{\psi_k}, \alpha_{\psi_k}, a_k, \text{ag}_j, \text{En}_{r_{\psi_k}}),$
 $\text{no-knowledge}(\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, \text{Vr}_{\psi_k}, \text{ag}_j, \text{En}_{r_{\psi_k}}).$

action $\text{retract}(\psi_i \in \text{Pr}_{\text{ag}_{\psi_i}}), \text{retract}(\psi_i \in \text{Pr}_{\text{ag}_j})$. All the agents that have ψ_i in their *Pr* will retract the illocution because we are dealing with a dialogue between multiple agents. An agent that shares the same preferences will answer with an “agree” so it does not make sense if that agent can use the same illocution again.

$\text{question}(\text{null}, \varphi_{\psi_i}, \alpha_{\psi_i}, \text{Vr}_{\psi_i}, \text{ag}_{\psi_i}, \text{En}_{r_{\psi_i}})$ is an illocution ψ_i in \mathcal{L}_c .

rationality the agent ag_{ψ_i} intends to perform a question when he wants to know about other agents' preferences.

dialogue $\forall \text{ag}_j \in \text{En}_{r_{\psi_i}}$ can:

$\text{prefer}(\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, \text{Vr}_{\psi_k}, \text{ag}_j, \text{En}_{r_{\psi_k}}),$
 $\text{no-knowledge}(\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, \text{Vr}_{\psi_k}, \text{ag}_j, \text{En}_{r_{\psi_k}}).$

action $\text{retract}(\psi_i \in \text{Pr}_{\text{ag}_{\psi_i}}), \text{retract}(\psi_i \in \text{Pr}_{\text{ag}_j})$. As we described in the “prefer” illocution, here the agents will also perform the same actions for the same reasons. Agents select whether to send a prefer or question illocutions based on their concern for self and concern for others. An agent has a higher probability to send a prefer illocution if his concern for self is higher than his concern for others. On the other hand, an agent has a higher probability to send a question illocution if his concern for others is higher than his concern for self. In case of agents without a defined behavior style, the illocution is selected randomly (50/50).

$\text{request}(\text{null}, \varphi_{\psi_i}, \alpha_{\psi_i}, a_j, \text{ag}_{\psi_i}, \text{En}_{r_{\psi_i}})$, where a_j is an alternative being requested in ψ_i which is an illocution in \mathcal{L}_c .

rationality the agent ag_{ψ_i} performs a request when he believes there is a reason for the other agent to accept it.

dialogue $\forall ag_j \in En_{r_{\psi_i}}$ can:

accept($\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, Vr_{\psi_k}, ag_j, ag_{\psi_i}$),

reject($\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, Vr_{\psi_k}, ag_j, ag_{\psi_i}$).

action retract($\psi_i \in Pr_{ag_{\psi_i}}$).

agree($\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, Vr_{\psi_k}, ag_j, En_{r_{\psi_k}}$)

rationality the agent ag_j informs about his agreement.

dialogue There is no dialogical sequence.

action $\forall ag_l \in En_{r_{\psi_k}}$ asserts Vr_{ψ_k} in $O_{ag_j K_{ag_l}}$. When an agent ag_j states his agreement about a ψ_i , other agents assert this information.

accept($\psi_i, \varphi_{\psi_k}, \alpha_{\psi_k}, a_i, ag_j, ag_l$)

rationality the agent ag_j informs about his acceptance.

dialogue There is no dialogical sequence.

action

ag_l asserts a_i in $O_{ag_j K_{ag_l}}$ and ag_j asserts a_i in O_{ag_j} and ag_j asserts ψ_m in Pr_{ag_j} , where ψ_l is an illocution indicating the preference regarding alternative a_i . The disagree, reject and no-knowledge illocution are not specified because they do not have any kind of consequences.

3.2. Requests

Throughout the dialogue agents exchange requests that can be followed by an argument (or not). To send a request an agent must decide what kind of request should be made. This depends on the knowledge acquired during the dialogue and that is associated with the preferences of other agents. The arguments that can be used in each request are of three types: appeal to self-interest, appeal to prevailing practice and appeal to common sense. The first two types were chosen based on literature and were first proposed by Kraus *et al.*⁴⁰ and were then adapted to later works in the area of argumentation. The third type is introduced in this paper and in the literature for the first time and is essential to make the negotiation process closer to what can be observed in real scenarios. It is common to find in the literature argumentation models that use argument types such as rewards or threats, however in our proposal we did not consider these types mainly because they cannot be used to discuss the problem's specific information. In fact, the information exchanged using these types of arguments may not be related to the problem at all. For example, an agent ag_1 threatening another agent ag_2 who does not want to go to restaurant a_1 by saying he will not be invited to future meetings does not bring more intelligence to the decision-making process, regardless of how it could help unlocking more conflictual situations. Our approach focuses entirely on a logic to achieve the best possible level of consensus while always maintaining the same level of concern towards the amount of

intelligence that can be generated. The idea is to support decision-makers using valuable knowledge instead of supporting fake consensual decisions every time this knowledge could be concealed. Below we move on to a more detailed description of each one of the argument types that have been considered.

Appeal to self-interest. This argument is used whenever an agent intends to convince another agent to accept a request claiming to be of his interest to accept it. This happens whenever an agent prefers a certain criterion and prefers an alternative which does not have the best values for the preferred criterion.

Example 1. Let us consider a car purchase example with two criteria $c_1 = \text{Price}$, $c_2 = \text{Durability}$, two alternatives $a_1 = (10000\text{€}, 8 \text{ years})$, $a_2 = (15000\text{€}, 10 \text{ years})$ and two agents ag_1 with $O_{\text{ag}_1} = \{a_2, c_1\}$ and ag_2 with $O_{\text{ag}_2} = \{a_1, c_1\}$.

Looking at ag_1 we know that his current objective is to choose the second alternative as the solution to the problem. However, since ag_1 prefers criterion c_1 then agent ag_2 is in condition to send a request message ψ_1 appealing to self-interest of ag_1 , where $\alpha_{\psi_1} = \text{"Accept } a_1 \text{ because } a_1 \text{ is cheaper than } a_2\text{"}$.

Appeal to prevailing practice. This argument is used whenever an agent intends to convince another agent to accept a request by referring to most participants which have already accepted the requested alternative.

Example 2. Let us consider the same car purchase example and this time there are five agents with the following objectives in time instant t : ag_1 and $O_{\text{ag}_1} = \{a_2\}$; ag_2 and $O_{\text{ag}_2} = \{a_2\}$; ag_3 and $O_{\text{ag}_3} = \{a_2\}$; ag_4 and $O_{\text{ag}_4} = \{a_1\}$; and ag_5 and $O_{\text{ag}_5} = \{a_1\}$. Both ag_1 , ag_2 , ag_3 prefer alternative a_1 and which means the total number of agents in favour of a_1 in time instant t corresponds to more than half of the total number of participants. Therefore, either ag_1 , ag_2 or ag_3 could send a request message ψ_1 to ag_4 or ag_5 appealing to prevailing practice, where $\alpha_{\psi_1} = \text{"Accept } a_2 \text{ because it has been accepted by more than half of the total number of participants."}$

Appeal to common sense. This argument can be used to convince an agent if he is the only one preferring a certain alternative while not accepting any other available alternatives. This can be seen in real situations whenever a participant is stuck with only one choice and refuses to accept different opinions thus becoming an obstacle to improve the flow of the discussion. At first glance, this argument might seem to be a type of appeal to prevailing practice, however if we look closer, we will see that both kind of arguments are completely different. An appeal to prevailing practice is an argument that involves an action performed by other agents. On the other hand, the appeal to common sense, involves an individual action which the agent who receives it did not perform yet.

Example 3. Let us consider the same car purchase example and this time there are 5 agents with the following objectives in time instant t : ag_1 and $O_{\text{ag}_1} = \{a_2\}$; ag_2 and $O_{\text{ag}_2} = \{a_2\}$; ag_3 and $O_{\text{ag}_3} = \{a_2\}$; ag_4 and $O_{\text{ag}_4} = \{a_2\}$; and ag_5 and $O_{\text{ag}_5} = \{a_1\}$.

Only agent ag_5 still has not accepted a_2 so all other agents ag_1, ag_2, ag_3, ag_4 could send a request message ψ_1 to ag_5 appealing to common sense, where $\alpha_{\psi_1} = \text{"You are the only one who has still not accepted } a_2\text{"}$.

3.3. Selection

Each request may include one of each type of arguments presented above and an agent may also send requests without arguments. Every time an agent exchanges new information, each other agent will process that information and verify if he can send a request or not. This request is not always targeted at the agent who shared the information. In fact, there may be situations where an agent may be able to send a request to someone else depending on the newly received information.

Example 4. Let us consider the same car purchase (considering five agents involved in the process) example and this time there is an agent ag_1 with $O_{ag_1} = \{a_2\}$, and he receives the following messages ψ_1 and ψ_2 , where $en_{s_{\psi_1}} = ag_2$, $\varphi_{\psi_1} = \text{"I prefer } a_2\text{"}$, $en_{s_{\psi_2}} = ag_3$, $\varphi_{\psi_2} = \text{"I prefer } a_2\text{"}$. This means ag_1 now knows three agents prefer a_2 and he could send a request message appealing to prevailing practice to ag_4 , even though ag_4 did not share any information.

Many proposed systems in the literature have been developed considering that an agent will always start by selecting another agent to send the request and only then will verify what type of argument is more adequate. In our proposal, we have chosen a different strategy where the agent will start by selecting the argument which we consider to be most persuasive (according to strength level of the type of that argument) and only then select the agent that will receive the request. The order of the arguments persuasion power is: appeal to common sense, appeal to self-interest, appeal to prevailing practice and finally simple request (request without an argument). This order is based on the definitions proposed by Kraus *et al.*⁴⁰ and the agent will always try to send requests starting with the argument which we consider to be stronger until no arguments can be selected and he is only allowed to make requests without an argument.

3.4. Restrictions

Let us define a function that returns the number of agents which agent ag_i knows that prefer alternative a_j in a time instant of t_k .

$$F_{\text{agentspreferalt}} : ag_i, a_j, t_k \rightarrow \forall ag \in K_{ag_i}, O_{ag} \supset a_j \wedge t_{K_{ag_i}} = t_k.$$

Now, let us assume that agent ag_1 sent a request message ψ_1 to another agent ag_2 to accept alternative a_1 in the time instant t_1 . Agent ag_1 cannot send another request message ψ_2 in the time instant t_2 , if:

$$\begin{aligned} En_{r_{\psi_1}} &= En_{r_{\psi_2}} = ag_2 \wedge Vr_{\psi_1} = Vr_{\psi_2} = a_1 \wedge \alpha_{\psi_1} \\ &= \alpha_{\psi_2} \wedge |F_{\text{agentspreferalt}}(ag_1, a_1, t_1)| \\ &= |F_{\text{agentspreferalt}}(ag_1, a_1, t_2)|. \end{aligned}$$

In other words, an agent must not send more than one request to accept the same alternative, to the same agent, with the same argument if the number of agents in favor of that alternative is also the same for each request. This stops agents from always sending the same request to the same agent which in turn will always refuse that request. On the other hand, this strategy allows agents reusing requests sent to the same agents under different conditions.

Now, let us define a function that returns the number of agents which agent ag_i still does not know their preferences in a time instant of t_k :

$$F_{\text{agentsnopref}} : ag_i t_k \rightarrow \forall ag \in K_{ag_i}, |O_{ag}| = 0 \wedge t_{K_{ag_i}} = t_k$$

An agent ag_1 cannot send a request message to ag_2 appealing to common sense at the time instant t_1 if $|F_{\text{agentsnopref}}(ag_1, t_1)| > 0$. This means that agent ag_1 still does not know the preferences for each participant in that time instant. This is done so that the agent does not use this type of request at the beginning of the discussion without knowing if more agents share the same preferences of the agent that would receive the request.

3.5. Evaluation

Our agents evaluate the requests with argument using subjective considerations.²⁹ This means that our agents use “its own preferences and motivations in making that judgement”.

An agent may accept or refuse a request depending on its resistance to change level. As mentioned before, resistance to change is one of the dimensions used to model agent’s style of behavior that we considered. With this, agents will make requests depending not only on their preferences but also on their style of behavior. In a very simple way we can say that the agent will:

Accept the request if:

$$\text{RAP} \geq \text{PAP} - \text{AI}, \quad (2)$$

where:

- RAP is the Requested Alternative Preference;
- PAP is the Preferred Alternative Preference;
- AI is the Acceptance Interval.

Refuse the request if:

$$\text{RAP} < \text{PAP} - \text{AI}. \quad (3)$$

The acceptance interval will vary depending on the resistance to change of the agent, the argument type and any variable related to the argument.

3.6. Request — without an argument

When evaluating a request without an argument this interval will be affected by the percentage of agents in favor of the requested alternative at the time it is received.

The formula used to calculate the acceptance interval for requests without arguments (4) is:

$$AI_{rwa} = (1 - \text{resistance}) * \frac{NAFRA}{TNA - 1}, \quad (4)$$

where:

- resistance is value of the resistance to change (of a specific behavior style);
- NAFRA is the Number of Agents in Favor of Requested Alternative;
- TNA is the Total Number of Agents.

That means requests will always be evaluated according to the context. The AI_{rwa} value for an alternative a_i increases as that alternative gains more supporters. The agent can accept the request (formula 2) if the preference for the requested alternative is higher than the difference between his most preferred alternative and the AI_{rwa} that is measured. For agents without a defined behavior we defined the value of resistance to change as 0.75.

3.7. Request — appealing to self-interest

When evaluating requests with the argument appealing to self-interest the acceptance interval is affected by the preference (normalized) of the agent towards the criterion associated to the argument plus the value of AI_{rwa} . The formula used to calculate the acceptance interval for requests with the argument appealing to self-interest (5) is

$$AI_{rsi} = ((1 - \text{resistance}) - AI_{rwa}) * CPN + AI_{rwa}, \quad (5)$$

where:

- CPN is the Normalization of the Preferred Criterion.

This allows the agent to widen its acceptance range according to the importance given to the criterion associated to the argument appealing to self-interest.

In case the agent does not have a defined behavior, the evaluation of the request with an argument appealing to self-interest will be done using the following formula:

$$AIWB_{rsi} = \left(\frac{NAFRA}{TNA} * CPN \right) * (1 - RAP) + RAP, \quad (6)$$

where:

- NAFRA is the Number of Agents in Favour of Requested Alternative;
- TNA is the Total Number of Agents;
- CPN is the Normalization of the Preferred Criterion;
- RAP is the Requested Alternative Preference.

3.8. Request — common practices

When evaluating requests with the argument appealing to common practices the acceptance interval is affected by the level of concern for others which the agent has towards the alternative plus AI_{rwa} . The formula used to calculate the acceptance interval for requests with the argument appealing to common practices (6) is

$$AI_{rcp} = ((1 - \text{resistance}) - AI_{rwa}) * CO + AI_{rwa}, \quad (7)$$

where:

- CO is the value of Concern for Others (of a specific behavior style).

In case the agent does not have a defined behavior, the evaluation of the request with an argument appealing to common practices will be done using the following formula:

$$AIWB_{rsi} = \left(\frac{NAFRA}{TNA} \right) * (1 - RAP) + RAP, \quad (8)$$

where:

- NAFRA is the Number of Agents in Favor of Requested Alternative;
- TNA is the Total Number of Agents;
- RAP is the Requested Alternative Preference.

3.9. Request — common sense

When evaluating requests with the argument appealing to common sense the acceptance interval will be the opposite of the resistance's level of the agent. The formula used to calculate the acceptance interval for requests with the argument appealing to common sense (7) is:

$$AI_{cs} = (1 - \text{resistance}). \quad (9)$$

The appeal to common sense is used in very specific situations. The agent that receives this request is the only agent which is still against a consensual decision. Therefore, the maximum acceptance interval will be used for the agent to verify if the requested alternative can be accepted.

In case the agent does not have a defined behavior, the evaluation of the request with an argument appealing to common sense will be done based on the difference between the number of agents in favor of requested alternative (NAFRA) and the the number of agents in favor of the preferred alternative (NAFPA). The agent will accept the alternative if:

$$NAFRA > NAFPA. \quad (10)$$

4. Evaluation and Results

In this section, we are going to describe all experiments that were conducted to evaluate the proposed work. We used a group of 12 virtual agents with different styles of behavior for each experiment. We conducted an exhaustive number of simulations to achieve solid results. We first detail the experimental settings and describe the types of agents we benchmark our framework against as well as the metrics used in our tests. Considering this, we provide the results of our experiments and go on to analyze the results under different agents’ configurations.

4.1. Experimental settings

In the considered scenario, agents negotiate to choose a desktop monitor for an organization. That organization intends to buy 200 new desktop monitors to one of its subsidiaries. Each agent represents one member of the organization administration board. This means agents must be cooperative because they all intend to choose the best decision for that organization and they also must be competitive because they aim to persuade other agents to accept what they believe that is the best decision (according to their configuration).

Table 3 represents the multi-criteria problem. Five possible alternatives have been identified. These alternatives have been classified according to five criteria: Size, Resolution, Hz, Ms and Price. Considering that we do not only evaluate criteria while trying to solve a multi-criteria problem, a decision-maker may prefer a certain alternative for subjective or unknown reasons that are not specified in the problem configuration.

We used the satisfaction and consensus levels as metrics to evaluate the overall performance in different scenarios. Satisfaction metric is used to measure the perception of the quality (of the decision-maker represented by the agent) towards the chosen alternative or the alternative supported by most agents during a certain moment. For this, we used the definitions proposed in Ref. 79 and the formulation used in Ref. 80. The level of consensus is measured according to the alternative that is supported by most agents in the time instant t , iteration i or round r . It is neither mandatory nor negative if agents cannot achieve a consensual decision by the end of the round. In fact, agents act according to an objective configuration logic and through a “social interaction” that portrays the interests of decision-makers.

Table 3. Multi-criteria problem.

Alternatives	Size	Resolution	Hz	Ms	Price
Asus 27" ROG SWIFT PG278Q	27	2560*1440	144	1	699,99€
BenQ 27" XL2720Z	27	1920*1080	144	1	489,00€
AOC 24" E2476VWM6	24	1920*1080	60	1	154,90€
BenQ 24" XL2430T	24	1920*1080	144	1	399,00€
LG 27" 27MP37VQ-B	27	1920*1080	60	5	210,80€

This means that if an agent does not accept a certain alternative then the decision-maker may still not be ready to accept it as well (although he may accept it in the future). That decision-maker should first analyze and think about the new information and eventually understand the situation and agree with it. Our approach does not intend to force a solution at all costs. Because of this, we use these two metrics (satisfaction and consensus) simultaneously. Our goal is to increase the levels of consensus without diminishing the levels of satisfaction in any possible way. Finding consensus while compromising the quality of the decision is not the solution.

The agents' preferences regarding alternatives and criteria, as well as their style of behavior, were randomly generated. However, in order for the evaluation of alternatives and criteria to make sense, the following approach was used, where each agent:

- (1) Randomly generated his preferences for each of the existing alternatives. Those preferences varied on the $[0,1]$ interval, where 0 means "Not at all preferred" and 1 means "Extremely preferred";
- (2) Selected the top preferred alternatives, i.e., those with the highest values;
- (3) Checked for those (top preferred) alternatives which criteria stand out, i.e., which criteria (comparatively) make sense to be valued in order to prefer those alternatives;
- (4) And finally, generated a random preference in a $[0.5,1]$ interval for those stood out criteria, and a random preference in a $[0,0.5]$ interval for the remaining criteria.

4.2. Experiments

In the first experiment, 35×101 simulations were performed. In each set of 101 simulations (let us call it a scenario) the preferences of each agent towards the problem (alternatives and criteria) were the same. Each simulation included 12 agents. In the first simulation, all 12 agents were configured without a defined behavior and in the following 100 simulations different styles of behavior were generated for each agent in each simulation. We then compared the obtained results between agents with a defined behavior in 100 simulations and agents configured without a defined behavior.

Figure 3 shows the satisfaction values obtained by agents without a defined behavior (AgWDB) and the average satisfaction values obtained by agents with a defined behavior (AgDB).

Since both AgWDB and AgDB average satisfaction values are being compared it is important to know what this average means. For that, Fig. 4 shows the number of times in which AgDB obtained a higher or lower satisfaction in each scenario. It is possible to identify that in most scenarios AgDB obtained a higher satisfaction. Counting all simulations performed in this experiment, the satisfaction was higher in 70.2% of the times and lower in 29.8% of the times. Another important point is

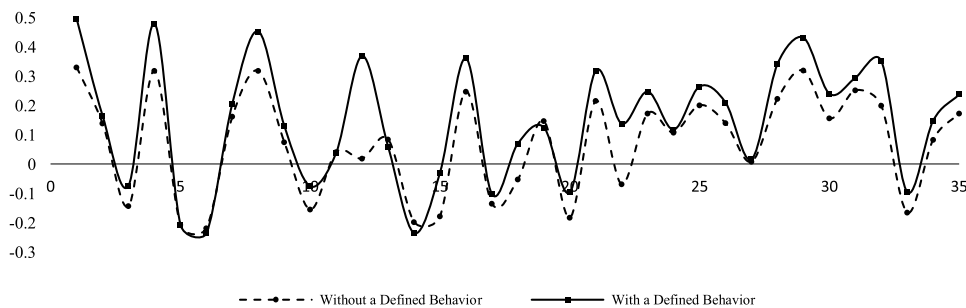


Fig. 3. Satisfaction values obtained in each scenario.

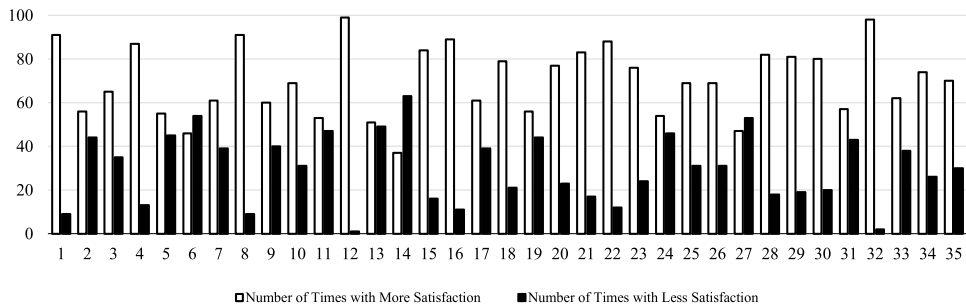


Fig. 4. Number of times when AgDB obtain more/less satisfaction than AgWDB in each scenario.

related with the obtained average satisfaction value. AgDB obtained in all simulations an average of 0.147 while AgWDB obtained just 0.069.

The impact of situations where AgDB obtained a higher or lower satisfaction compared to AgWDB was also studied. It was important to know if there was a big difference when AgDB obtain a lower satisfaction compared to AgWDB. Figure 5 shows the results between the average gain and loss of satisfaction of AgDB and AgWDB. In 70.2% of the times where AgDB obtained a higher satisfaction, the

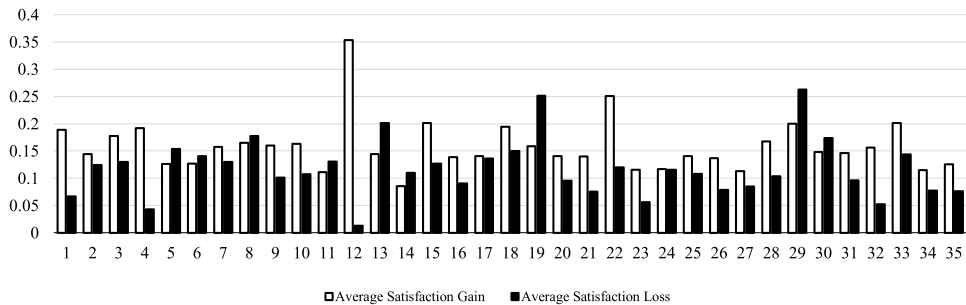


Fig. 5. Gain/loss of satisfaction every time AgDB obtain more/less satisfaction than AgWDB.

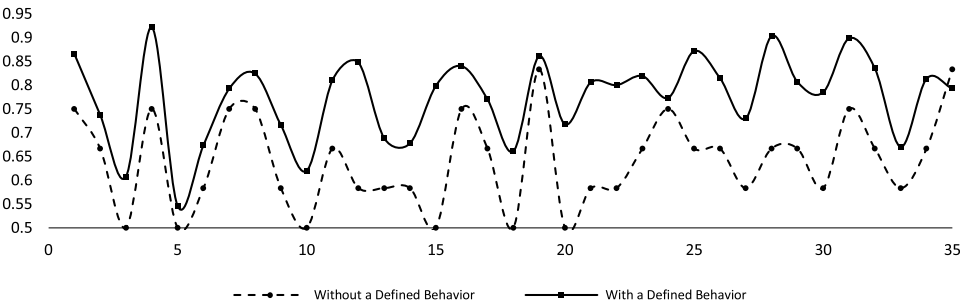


Fig. 6. Consensus values obtained in each scenario.

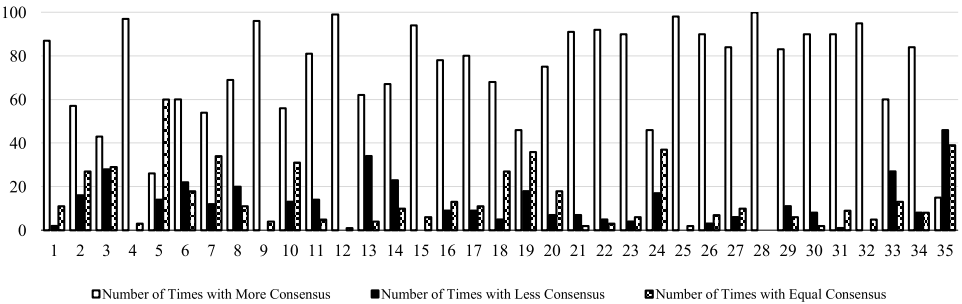


Fig. 7. Number of times when AgDB obtain more/less consensus than AgWDB in each scenario.

average gain was of 0.158, however in 29.8% of the times where AgDB obtained a lower satisfaction, the average loss was of 0.117.

Figure 6 shows the consensus values obtained by AgWDB and the average consensus values obtained by AgDB in each scenario. It is possible to see that AgDB also a higher consensus compared to AgWDB in most of the times.

Figure 7 shows the number of times in which AgDB obtained more/less/same consensus than AgWDB. AgDB obtained a higher average consensus in 74.3% of the times, equal in 14.5% of the times and lower in 11.1% of the times.

As we did in the satisfaction analysis, the impact of gain and loss of consensus was also analyzed in situations where the consensus is higher or lower, respectively. Figure 8 shows the results that were obtained. As can be seen, the gain of consensus is higher (0.192 average) when the consensus obtained is also higher and the loss is lower (0.091 average) when the consensus obtained is also lower.

In the second experiment, 35*6 simulations were performed. In each scenario agents had different problem configurations (regarding alternatives and criteria). For all six simulations in the same scenario agents' configurations were the same. In each simulation, 12 agents were used and were all defined with the same style of behavior (1st Simulation — 12 AgWDB, 2nd Simulation — 12 agents Integrating, 3rd Simulation — 12 agents Obliging, 4th Simulation — 12 agents Dominating, 5th Simulation — 12 agents Compromising and 6th Simulation — 12 agents Avoiding).

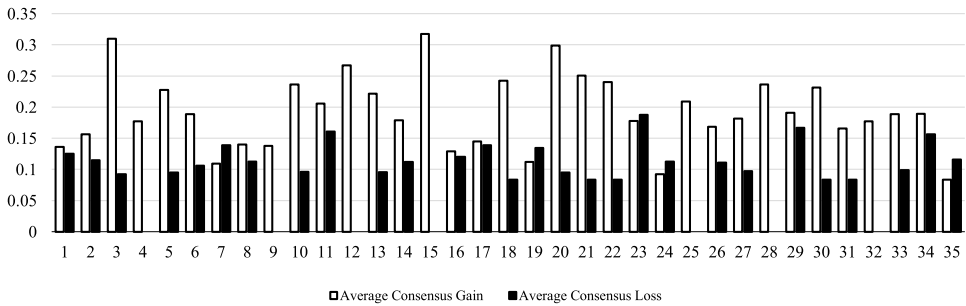


Fig. 8. Gain/loss of consensus every time AgDB obtain more/less consensus than AgWDB.

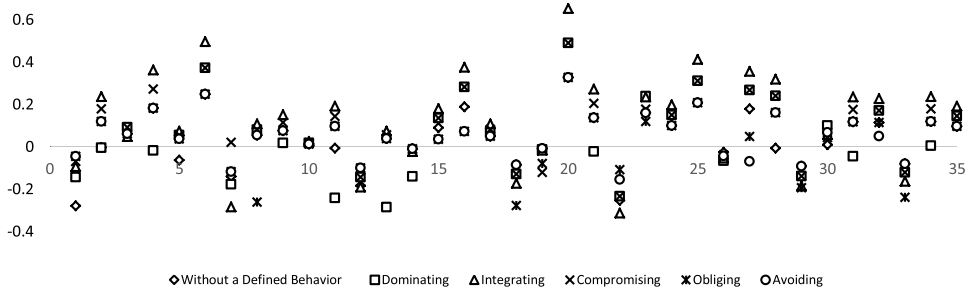


Fig. 9. Satisfaction obtained in each scenario.

Figure 9 shows the satisfaction results obtained by agents with the same style of behavior throughout all 35 scenarios. Integrating agents achieved higher satisfaction levels compared to other agents while it seems that Dominating agents, on the opposite turn, obtained the lower satisfaction levels. The average satisfaction values obtained for each style of behavior were the following: Integrating — 0.122; Compromising — 0.097; Avoiding — 0.05; Without a Defined Behavior — 0.036; Dominating — 0.036 and Obliging — 0.031.

Figure 10 shows consensus values obtained by agents in each simulation. It is possible to see that both Obliging and Avoiding agents obtained the same consensus most of the times (value 1 which means they achieved a consensual decision) and therefore appear overlaid. In this experiment, it was possible to identify that Obliging and Avoiding agents always obtained the highest consensus, Dominating agents obtained the lowest consensus and the remaining styles of conflict obtained intermediate values. Besides this, and looking at the graph, the consensus values obtained by each group of agents with the same style of behavior are very consistent throughout all 35 scenarios, even if agents' configurations were different in all of them. The average consensus for each style of behavior for each scenario was the following: Obliging — 0.959; Avoiding — 0.945; Integrating — 0.73; Compromising — 0.728; Without a Defined Behavior — 0.609 and Dominating — 0.39.

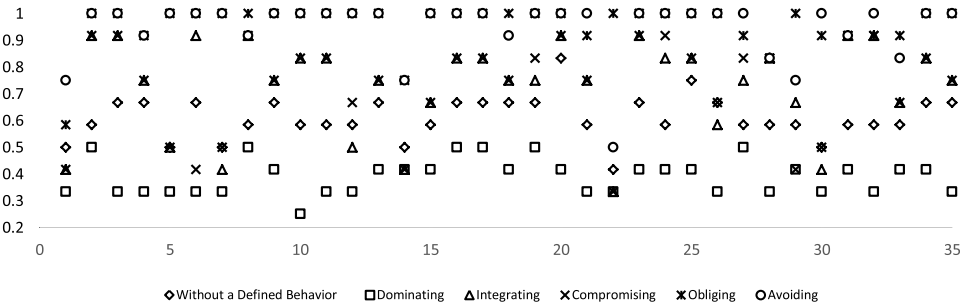


Fig. 10. Consensus obtained in each scenario.

5. Discussion

In this section, all the hypotheses are discussed. The first hypothesis is the most important and is the reason for all the experiments performed in this work. The other hypotheses were identified as the study progressed. Given this, we postulate several hypotheses regarding the performance and behavior of the agents.

Hypothesis 1. Agents that represent/support decision-makers in the ubiquitous group decision-making process and that use styles of behavior can obtain higher consensus and quality decisions more easily.

AgDB obtained higher satisfaction levels compared to AgWDB in 70.2% of the simulations and obtained higher consensus levels in 74.3% of the times. Besides this, it was also verified that in the 70.2% of the times when the satisfaction obtained is higher, there was a gain of satisfaction that was superior (0.158) to the loss of satisfaction (0.117) in the remaining 29.8% of the times when the satisfaction obtained is lower. These results were very positive. In the case when the consensus obtained was higher, the gains were even more significant. Not only do agents obtained higher consensus in more simulations (89.9%), the gain was also higher (0.192). On the other hand, the consensus obtained was lower in the remaining 11.1% of the times with a loss of 0.091. With these results confirmed we have all the necessary conditions to accept the formulated hypothesis.

Hypothesis 2. Agents with a higher level of concern for others obtain higher satisfaction levels.

This hypothesis was rejected. Integrating and Obliging are the styles of behavior with the highest level of concern for others, followed by Compromising style, and lastly Avoiding and Dominating styles. The hypothesis was rejected since Obliging agents achieved low average satisfaction levels when agents with the same style of behavior were being studied. By rejecting this hypothesis, we did formulate a new one (Hypothesis 2.1).

Hypothesis 2.1. Agents that are naturally more competitive and collaborative obtain higher satisfaction levels.

If we make a purely comparative analysis (as done in the second experiment) we can accept this hypothesis. We verified that Integrating and Compromising styles, which have very similar concern for self and concern for others values, achieved the highest levels of satisfaction. This may lead us to think that other styles only harm the process. However, (as can be seen) in the first experiment (when we used agents with all sorts of styles) agents achieved an average satisfaction level of 0.147 which is superior to the value obtained by Integrating agents (0.122). This let us conclude that the diversity of styles of behavior allows obtaining higher satisfaction levels compared to the situation where all agents share the same style. Considering that we live in a diversified reality, this hypothesis would be rejected. This conclusion allows formulating a new hypothesis that was not studied in this work: Obliging agents, due to their high level of concern for others and low level of concern for self, are especially useful in scenarios where other agents with different styles of behavior also participate. The study of Obliging agents is a paradox.

Hypothesis 3. Agents with a low concern for self obtain consensus more easily.

Obliging and Avoiding agents have the lowest level of concern for self, followed by Compromising agents while Integrating and Dominating agents have the highest level of concern for self. If we just look at the concern for self we are forced to reject the hypothesis, because Integrating agents have a higher concern for self compared to Compromising agents but still obtain slightly higher average consensus levels. However, we have identified a pattern that let us explain this situation. Obliging agents obtained higher average consensus levels compared to Avoiding agents even though both styles share almost the same level of concern for self. However, since Obliging agents have higher level of concern for others this let us believe that in situations where agents with the same concern for self will obtain higher consensus levels if they have a higher concern for others. This explains why Integrating agents obtain slightly higher consensus levels compared to Compromising agents.

Hypothesis 4. Using agents defined with a style of behavior is always advantageous.

This hypothesis has been rejected because we can see in the second experiment Dominating agents obtained worse satisfaction and consensus values compared with AgWDB. This means that in a hypothetical situation in which all decision-makers choose the Dominating style of behavior they would obtain worse results in case we did not use any kind of behavioral modeling. However, we consider that a situation in which all agents are defined with the Dominating style can still generate valuable knowledge that can be used in the future to support the group decision-making process in that kind of scenario. On the other hand, when we only deal with AgWDB we cannot generate and use such kind of knowledge.

It is also important to relate this work with current literature. As referred before, our argumentation-based dialogue model aims to support the group decision making process. Our approach is very different to what can be found in literature. This is because our model was defined in order to take advantage of what the benefits

associated with the group decision-making process are. Thus, contrary to what happens in most of the existing proposals,^{81,82} our model deals with several types of dialogue, since, despite the goal to achieve consensus, there is also the goal to enhance the quality of the decision. Therefore, our model focuses not only on dialogue types such as negotiation or persuasion, but also on strategies that allow agents to discover new information and perceive the reasons for the preferences of other decision-makers.

The difference of the proposal presented in this work is also distinguished by the way it is validated. A lot of works are validated using the Seller/Buyer example^{37,83,84} which is a context completely different from the one presented in this work. As we said, we do not want to make a deal, nor want agents to reach a consensus at any costs. Our model aims to support the decision-making process by using and creating new knowledge. Our work takes advantage of the typical benefits inherent to group decision-making and proved that it is possible to obtain results that follow that perspective. That is why we included in the evaluation phase both metrics, the level of consensus and the level of satisfaction.

Other authors with a relevant work in this area considered in very recent papers that most the work found in the literature related to argumentation-based decision-making did not pay attention to decision-making amongst multiple agents. In fact, Fan and Toni⁸⁵ refer to the necessity of studying “decision-making in the context of multiple agents, in which agents may share potentially conflicting knowledge and preferences”. In our work, besides proposing a model that supports multiple agents interacting in a very similar way as humans do in face-to-face meetings, the created prototype had an exceptional performance without presenting any sort of issues.

One of the main points of this work is the capacity the agents start to have to represent the intentions of the decision-makers. Although there are some works in the field of decision-making in which the authors try to make this type of representation,^{20,33,59,70} it is done in a very ambiguous way, where the values of performance of those styles are not scientifically validated, being merely indicative and approximations of what is thought to make sense. In addition, they do not validate in a real system if the decision-makers would be able to configure and understand the objectives of each of those styles. Although it is obvious that it would be advantageous to include affective components in this type of context, it had never been proved as it happens in this work.

Finally, it is not less important to mention the potential that the proposal here presented has to document and explain the reasons that lead to a certain decision. Muller and Hunter⁸⁶ consider that it is very important that argumentation models can generate documentation and also explain why certain decisions are made. Our approach is also clear to the decision-maker and allows him to understand the process and properly explains the reason why a certain solution is decided. Knowing how agents communicate with each other, the text composing each locution could be used to make that documentation.

6. Related Work

Black and Hunter⁸¹ presented a framework for representing dialogues of the type inquiry. Their argumentative system is based in Defeasible Logic Programming (DeLP). In their work, they consider two types of inquiry dialogues: argument inquiry and warrant inquiry. The former intends that agents can jointly construct arguments to support a particular claim that would not be possible if done separately (alone). The latter intends that agents can share arguments in order to construct a dialectical tree that they could not do alone with their own beliefs. In these two types of inquiry dialogues, agents jointly seek to inquire about topics. However, the argument inquiry dialogue does not allow to determine the acceptability of the constructed arguments, and in case of the warranty inquiry dialogue the agents work together to determine the acceptability of the arguments (they do this by jointly constructing a dialectical tree). The authors named the communicative acts as “moves”. They considered the existence of three different moves: open, assert and close. A move is represented as $\langle \text{Agent}, \text{Act}, \text{Content} \rangle$, where Agent is the agent generating the move, Act is the type of the move and Content contains information about the details of the move. The dialogue is always performed by exactly two agents and always starts by an “open” move. They represent the first move as $\langle x \text{ open}, \text{dialogue}(\theta, \gamma) \rangle$, where θ is the type of the dialogue and γ is the topic of the dialogue. So, the type and the topic of the dialogue are defined in the content of the first move. The dialogue ends when both agents make the “close” move.

Prakken⁸² proposed a formal framework of argumentation dialogues for persuasion. In his work, he presents an example of a persuasion dialogue, which we present below:

- (1) ag_1 : My car is very safe. (*making a claim*)
- (2) ag_2 : Why is your car safe? (*asking grounds for a claim*)
- (3) ag_1 : Since it has an airbag. (*offering alternative grounds for a claim*)
- (4) ag_2 : That is true, (*persuasion: conceding a claim*) but I disagree that this makes your car safe: the newspapers recently reported on airbags expanding without cause. (*stating a counterargument*)
- (5) ag_1 : Yes, that is what newspapers say (*conceding a claim*) but that does not prove anything, since newspaper reports are very unreliable sources of technological information. (*undercutting a counterargument*)
- (5) ag_2 : Still your car is still not safe, since its maximum speed is very high. (*alternative counterargument*)

This example demonstrates the complexity of the persuasion dialogues. As we can see, during a dialogue of this type, an individual/agent can refer back to previous choices in the same dialogue, as well as justify a certain point of view in different ways.

In his work, Prakken⁸² introduced the “liberal” and “relevant” dialogue systems. Table 4 presents the moves for liberal dialogues.

Table 4. Speech acts for liberal dialogues (adapted from Prakken Ref. 82).

Acts	Attacks	Surrenders
claim φ	why φ	concede φ
why φ	argue $A(\text{conc}(A) = \varphi)$	retract φ
argue A	why $\varphi(\varphi \in \text{prem}(A))$ argue $B(B \text{ defeats } A)$	concede φ ($\varphi \in \text{prem}(A)$ or $\varphi = \text{conc}(A)$)
concede φ		
retract φ		

As in the work of Black and Hunter,⁸¹ Prakken's liberal dialogues are represented as trees and the arguments of a tree are always relative to only one topic. An argument is a deduction with a conclusion (conc) and premises (prem), and "An argument B extends an argument A if $\text{conc}(B) = \varphi$ and $\varphi \in \text{prem}(A)$ ". The author also defined a turn-taking function that specifies which agent does the next move, which basically guarantees the existence of a "ping-pong" dialogue, where the first move is responsible for specifying the dialogue's topic. One of the most relevant parts of this work is the way Prakken determines the outcome of a dialogue by defining an in/out labeling. Theoretically, what happens is that a node is in if it withstands its attacks, otherwise it is out. So, considering that the root of a dialogue is responsible for defining the topic, the proponent wins the dialogue if the root node is in.

Parsons *et al.*⁸⁷ presented a study about argumentation-based dialogues between agents. They have defined locutions from which agents can exchange arguments. In addition, agents may adopt different attitudes which will condition the arguments that they can build and what locutions they can make. They also defined a set of protocols which determine the entire functioning of the dialogue (termination, dialogue outcomes and complexity). In this work, they deal with three types of dialogues: information seeking, inquiry and persuasion. They assume the dialogues are always performed by only two agents, which can use several utterances, such as: assert, accept, challenge and question. One of the most fascinating points of this work is the relation defined between the agents' attitudes and their way of acting. For instance, an agent can have three different assertion attitudes: confident, careful and thoughtful, and three acceptance attitudes: credulous, cautious and skeptical.

Next, an example of a possible information seeking dialogue is presented, using the protocol proposed by the authors:

- (1) ag_1 asks $\text{question}(p)$;
- (2) ag_2 replies either $\text{assert}(p)$ or $\text{assert}(\neg p)$ if it can, and $\text{assert}(\mathcal{U})$ if it cannot. Which response is given will depend upon the contents of its knowledge base and its assertion attitude. \mathcal{U} indicates that, for whatever reason, \mathcal{B} cannot give an answer;
- (3) ag_1 either accepts \mathcal{B} 's response, if its acceptance attitude allows, or challenges. \mathcal{U} cannot be challenged and as soon as it is asserted, the dialogue terminates without the question being resolved;

- (4) ag_2 replies to a challenge with an $\text{assert}(\mathcal{S})$, where \mathcal{S} is the support of an argument for the last proposition challenged by ag_1 ;
- (5) Go to 3 for each proposition in \mathcal{S} in turn;
- (6) ag_1 accepts p if its acceptance attitude allows.

There is a large number of applications of dialogue systems in literature^{34,88,89} covering various topics, such as: resource-bounded reasoning,^{90,91} legal reasoning,^{92,93} to support agent interaction^{87,94} among others. However, argumentation-based dialogue models specifically targeted at the context of group decision-making and that benefit from group decision-making are practically nonexistent.

Many approaches have been put forward in literature, where agents are defined with characteristics that set them apart from each other.^{95–98} Also under the topic of group decision-making several works with agents have been proposed,^{99,100} some of which used agents as a way to represent decision-makers/experts.^{33,59,101} This representation of decision-makers allows the systems to become more intelligent and dynamic, given that they are capable of dealing with aspects of great relevance in face-to-face type meetings. Next, we will see some works in the context of the decision-making that present strategies to represent the decision-makers.

Santos *et al.*⁵⁹ presented a scientific work where they proposed a multi-agent architecture model designed to support groups in the decision-making process. The novelty of their work is the possibility to model the agent's personality. The idea is to humanize agents and with that, facilitate the negotiation process. They used four personality types (Negotiator, Aggressor, Submissive and Avoider) based on the Five Factor Model¹⁰² to define the agents' personalities. To select the agent's personality, each decision-maker needs to answer a questionnaire named Big Five Inventory.¹⁰³ They also proposed a simple negotiation model where the agents use the personalities to choose which kind of requests they should send and to process the received requests. The publication does not include any case study; however, the content is very interesting because the proposed model is based in strong assumptions existent in the literature.

Palomares *et al.*⁷⁰ presented a Web-based consensus support system that permits the integration of the decision-makers' attitude regarding consensus. They study the importance that decision-makers place in reaching consensus regarding the possibility of modifying their own preferences. Decision-makers can/adopt three attitudes: pessimistic, indifferent and optimistic. For example, a decision-maker who adopts an optimistic attitude, means that for him to reach the agreement is more important than his own preferences. As a result, the group's options will be given more importance. They argue that (as might be expected) optimistic attitudes help to reach consensus while pessimistic attitudes hamper the achievement of consensus.

Recio-García *et al.*⁷¹ presented a group decision support system where each decision-maker is represented by an agent who argues with the other agents in order to achieve the best alternative for the group. The presented negotiation model includes the users' social factors, personality and trust in the argumentative process.

The personality of decision-makers is represented by a number ranging from $[0,1]$ where 0 means a very cooperative person and the reflection of a very selfish one. To study the concept of trust, they use the interaction of decision-makers in social networks through a set of 10 factors. For the argumentation model, they used D²ISCO, which is a platform for the design and implementation of deliberative and collaborative CBR applications. They concluded that the proposed model allows to achieve better satisfaction rates when compared to the standard “fully connected” group recommender.

Palomares and Martínez³³ presented a semisupervised consensus support system (CSS) based on the multi-agent system paradigm. The main purposes are to overcome the difficulties associated with managing large groups of experts and the need for constant human supervision. In order to minimize the need for experts’ interactions with the system, they defined a strategy that allows the experts to express their individual concerns. To do so, they defined three different profiles: sure profile, unsure profile and neutral profile. The first, intends to represent experts that are very confident about their preferences. Therefore, they do not intend to change them. The second, represents experts that want to achieve a consensus but are unsure about their opinions. The third, represent the experts that want to achieve a consensus and are moderately sure about their opinions. They conducted a case study made up by a set of experiments with the intent of understanding the different evolution of the degree of consensus between the proposed semisupervised CSS and a full-supervised CSS. They concluded that through the proposed system it was possible to minimize the need for expert human supervision and more importantly, they concluded that their proposal helps to achieve high levels of consensus faster than the full-supervised CSS.

7. Conclusions and Future Work

The future and success of organizations depend greatly on the quality of every decision made. It is known that many of the decisions taken inside organizations are made in group. To support this type of decision, the Group Decision Support Systems (GDSS) have been widely studied throughout the last decades. However, in the last 10/20 years, we have seen a remarkable change in the context where the decision-making process happens, especially in large organizations. With the appearance of global markets, the growth of multinational enterprises and a more global vision of the planet, we easily find chief executive officers and top managers (decision-makers) spread around the world, in countries with different time zones. To provide an answer and to operate correctly in this type of scenarios the traditional GDSS have evolved to what we identify today as Web-based Group Decision Support Systems (Web-based GDSS). The idea behind the Web-based GDSS is to support the decision-making process “anytime” and “anywhere”. However, supporting groups in this context is a very complex task. It is necessary to create conditions in which the decision-maker can acknowledge the advantages of using the

system and feels motivated to do so. The system must allow the decision-maker to express himself and this includes problem and communication configurations. We must keep in mind that the best algorithm will fail if the final user does not want to use it. Besides this, a Web-based GDSS must support decision-makers throughout the decision-making process until the best solution can be found. This support includes not only obtaining consensus but also the best possible solution. Therefore, strategies that “hide” information just to achieve a faster solution must not be used.

In this work, we propose an argumentation-based dialogue model for Web-based GDSS. This model provides a set of features that let us take advantage of the known benefits inherent to group decision-making. Our proposal allows agents to interact in a very similar way as humans do in face-to-face meetings. Each agent represents a real decision-maker and will attempt to defend his interests and persuade other agents according to the knowledge he possesses. However, agents do not persuade “foolishly” as they will be guided by the style of behavior defined by their decision-maker. Decision-makers may select five different styles of behavior which define how their agent will behave and act throughout the decision-making process, resulting in a better representation of their interests and objectives. Each style of behavior proposed in this work has been defined according to four dimensions. To figure how agents will act in each dimension, real results were used and analyzed how people expect an agent to behave depending on his style of behavior. This means that when a decision-maker selects a certain style of behavior for his representing agent he is unconsciously sharing information with the system.

We proposed a model that works well when multiple agents communicate and interact with each other. Second, our work takes advantage of the benefits inherent to group decision-making. Our proposal lets decision-makers recognize the importance of the process. Third, and most importantly, with this work we have proved the prevalence of using styles of behavior in this type of context. Our approach allows decision-makers not only to configure their preferences but also their intentions (for instance: strategies and interest in the process). With this, we could conclude many details explained previously, as for example, why agents with a high concern for others tend to obtain higher satisfaction levels as well as agents with low concern for self tend to obtain higher consensus levels. However, although we could identify these tendencies, we also saw the system can reflect the positive and typical diversity of human interactions. If we do not forget that the real world is diversified, and that diversity is a benefit, then our approach does not lead to a very inflexible system but rather to a system that can take advantage of it.

As future work, we intend to study ways to deal with complex situations. We consider a complex situation, for example, a scenario where all agents have the Dominating style of behavior. The idea is to take advantage of the previous knowledge that tells us how difficult it is to achieve a consensual decision in that context and find specific mechanisms for that kind of scenarios. These mechanisms should follow the logic applied to this work meaning the goal should always be to seek consensus through the free exchange of knowledge and motivate the decision-makers

to understand arguments exchanged by other decision-makers. Another question we intend to study is how the entire decision-making process (and not only a simple iteration as studied in this work) using our framework model allows us to achieve even higher levels of consensus and satisfaction.

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