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Abstract. Agent-based simulation has long been used to study the dynamics of adoption and diffusion of innovations. However, the vast majority of these works are limited to an abstract and simplified representation of this process, which does not allow to explain the reasons for the change of opinion of an agent. In order to go further in the explanation of these changes, we present a generic model based on the theory of planned behavior and on formal argumentation. Each agent has the possibility to exchange arguments with another and to build its opinion on an innovation from the set of arguments it knows. An application of the model is proposed to study the adoption of communicating water meters by farmers on the Louts river (South-West of France).

Keywords: Agent-based simulation, Diffusion of innovation, Argumentation, Theory of planned behavior

1 Introduction

Many studies have already focused on modeling the process of innovation diffusion. A natural way of studying such a process is to use agent-based modeling [10], each agent representing an individual that can influence the others on their adoption of the innovation. However, most of these models represent the opinion of each agent on an innovation by a numerical variable that evolves directly during their interactions with other agents. This type of representation provides little information on the change of opinion of the agent as the reasons for its change are not known.

To overcome this limitation, a relevant framework is the formal argumentation [1]. Argumentation deals with situations where information contains contradictions because it comes from several sources or corresponds to several points of view that possibly have different priorities. If several agent-based models already integrate argument exchanges to represent opinion dynamics processes [11, 13, 18, 8, 15], to our knowledge, no model proposes to explicitly integrate arguments to simulate the innovation diffusion process.

We therefore propose in this paper a generic model in which the knowledge of each agent is explicitly represented in the form of arguments, which carry information about the innovation. These arguments are the objects that the agents will exchange during their interactions. The advantage of this approach is that it allows one to trace the state of knowledge of an agent in order to understand the evolution of its behavior in front of an innovation. We also propose to represent the decisional model of the agents with the Theory of Planned Behaviour (TPB). This theory, very classical in psychology, offers an integrative framework to formalize the behavior of agents [9, 2].

2   Related works

Zhang & Vorobeychik [20] proposed a critical review of innovation diffusion models in 2019. In doing so, they proposed to categorize these models based on how the models represent the decision to adopt. Among these categories, we can distinguish cognitive agent models that are closest to our concerns: they aim to explicitly represent how individuals influence each other in cognitive and psychological terms. A particularly popular model in this category is the *relative agreement* model of [6]. This model, which builds on Rogers' observations [12], focuses on the notion of opinion about an innovation. The individual's opinion and uncertainties are represented by numerical values that evolve during interpersonal interactions.

While no model of innovation diffusion has used the concept of argument, in the field of opinion dynamics, several works have tried to better represent the impacts of interpersonal interactions on opinion through the use of this concept. Some of these works such as [11] propose a simple formalization of arguments in the form of a numerical value. Although these works show interesting results on processes such as bipolarization, they do not provide information on argumentative reasoning and do not explicitly represent the tensions between arguments.

To overcome this limitation, several works such as [8, 17, 4, 15] have proposed the use of the system introduced by Dung [7]. These works illustrate the interest of using such a formalism to represent arguments in the framework of an opinion dynamics model. Among these works, [15] is particularly interesting for us because they propose a complete process of opinion construction from arguments, which allows to easily integrate the heterogeneity of the agents through the explicit representation of the point of view of each agent on certain topics (e.g. environment, economy, etc.).

We therefore propose to take up, within the integrative framework of the theory of planned behavior, the basis of the innovation diffusion model proposed by [6] and to integrate argumentation to represent the cognition of agents. Concerning argumentation, we used a model close to the one proposed by [15] by enriching it to integrate, among other things, the notions of trust in sources.

3 Proposed model

3.1 Arguments

Arguments are the objects that represent the pieces of information about the innovation that agents can understand and exchange. While Dung considers arguments as abstract objects with no descriptive data, other works propose to extend this concept by adding semantics to arguments [15, 16, 3]. In this work, we have chosen to use the representation proposed in [15] in which the data composing the argument plays the role of support in the knowledge evaluation.

An argument is a tuple (I, O, T, S, C, Ts) :

- I: the identifier of the argument
- O: the option concerned by the argument
- T: the type of argument (pro: +, con: -)
- S: the proposition of the argument
- C: the criteria (themes) linked to the argument
- Ts: the type of the source of the argument

Arguments are linked together by the notion of attack. An attack happens when an argument challenges another argument. For more details on attacks, see [19].

3.2 The agents

The model is composed of agents *individual*, which represent the potential adopters of an innovation. The decision model of these agents is based on the TBP which is based on the notion of intention to behave for an individual. This intention is derived from 3 variables: attitude, subjective social norm, and perceived behavioral control (PBC). The attitude represents the knowledge and opinion that an individual has about a behavior (in our case the use of innovation). The subjective norm is the individual's perception of the adoption intention of her/his social network. Finally, the PBC is the capacity felt by the individual to adopt the behavior (in terms of cost, time, skills, technical aids, ...).

The intention can thus be calculated with the values of these 3 variables. Weighting each variable according to its importance, [9] propose the following equation to calculate the intention:

$$I_i = w_i^a a_i + w_i^s s_i + w_i^p p_i \tag{1}$$

with: I_i the intention of agent i, a_i s_i p_i respectively the values of attitude, subjective norm and PBC of agent i and w_i^a w_i^s w_i^p respectively the weights of attitude, subjective norm and PBC of agent i.

Our proposal is to compute the attitude of the agents from their knowledge about the innovation, modeled as an argument graph. Concerning the subjective norm, we propose to draw inspiration from the work of [5], who suggests that during an interaction between two individuals the influence of one on the other depends on the opinions and certainties they have on the subject.

Concerning the PBC, which is specific to the type of innovation studied and to the individual concerned, we propose to transcribe it in the form of a variable specific to each individual, which may or may not be constant depending on the case of application.

We also define the notions of uncertainty on the attitude and the subjective norm through two real variables between 0 and 1 (0: total certainty, 1: total uncertainty). From these two variables, we define the uncertainty on the intention calculated as follows. Let u_i^a and u_i^s be respectively the uncertainties of the agent i on its attitude and subjective norm values, the uncertainty on the intention u_i^I is defined by:

$$u_i^I = \frac{u_i^a w_i^a + u_i^s w_i^s}{w_i^a + w_i^s} \qquad (2)$$

Thus, each agent has the following attributes:

- *argument graph*: an argument graph where the vertices are the arguments known by the agent and each weighted arc represents an attack from one argument to another with the value of the attack strength for the agent;
- *informed*: boolean indicating if the agent has enough arguments (n_{args}) to evaluate its individual benefit;
- *importance of the criteria*: each criterion (theme) of the arguments (C of an argument) is linked to a real value between 0 (unimportant) and 1 (very important) which represents its importance for the agent;
- *trust in the source type*: each type of argument source (Ts element of an argument) is linked to a numerical value between 0 (no trust) and 1 (total trust) which represents the agent's trust in the type of source;
- *neighbors*: all the agents with which it is linked through the social network;
- *attitude*: real value between -1 and 1 that quantifies the benefit that the innovation brings to the agent (-1 very negative effect; 1 very beneficial);
- *attitude uncertainty*: real value between 0 and 1 that represents its uncertainty about its personal benefit. A value close to 0 means little uncertainty and vice versa;
- *subjective social norm*: real value between -1 and 1 which corresponds to an estimate of the opinion that other agents have of the innovation (-1 very bad opinion; 1 very good opinion);
- *uncertainty about the subjective social norm*: A real value between 0 and 1 that represents the uncertainty about one's subjective norm. A value close to 0 means little uncertainty and vice versa;
- *weight of the attitude in the calculation of the intention*: real value representing the influence of attitude in the calculation of intention;
- *weight of the subjective norm in the calculation of the intention*: real value representing the influence of attitude in the calculation of intention;
- *weight of PBC in the calculation of intention*: actual value representing the influence of attitude in the calculation of intention;
- *intention*: real value between -1 and 1 calculated from attitude, subjective norm, and PBC;

- *intention uncertainty*: Actual value between 0 and 1 calculated from attitude uncertainty and subjective norm uncertainty;
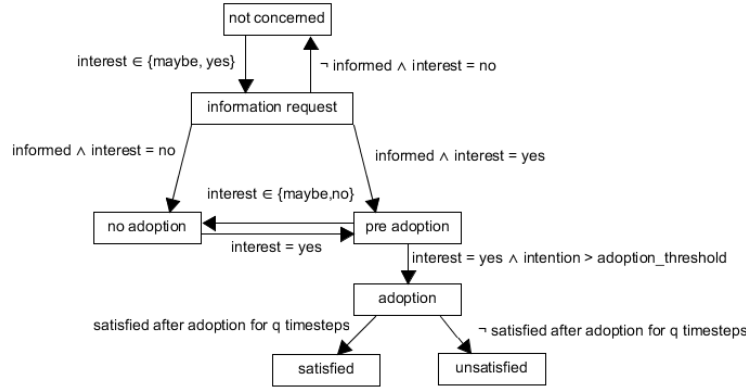- *decision status*: represents the agent's adoption state (See Figure 1).

Fig. 1. Agent's decision process

3.3   The dynamics of the model

At each simulation step, 4 processes are executed in the following order:

1. New arguments coming from an external source (advertisement, specialized press article...) are added to the arguments of the agents seeking information, *i.e.* in the state *information request*.
2. Each agent having received arguments revises its beliefs according to its new internal argumentation graph to compute its new attitude and intention value then its adoption state.
3. Each agent, according to its information state and intention, can exchange one or more arguments with its neighbors.
4. The agents revise their beliefs a second time to update their decision variables.

Concerning the first step, an agent can become aware of an argument, mobilize it during interactions, but also forget it. Indeed, empirical research suggests that people have limited abilities to remember information. As in the ACTB model [11], we consider that the number of arguments with which an agent can form an opinion is limited and the agent forgets the arguments that it has not mobilized during a given time; its memory is thus represented as a queue.

Concerning Step 2 and 4, the revision of beliefs is based on the notion of strength of an argument for an agent. For an agent i, the strength $F_i(a)$ of an

argument a is defined by:

$$f_i(a) = conf_i(a) \sum_{c \in C} a_c \times i_c \qquad (3)$$

with C the set of criteria, a_c the value of criterion c for argument a, i_c the importance of criterion c for agent i and $conf_i(a)$ the confidence that agent i has in the source type of argument a.

From the notion of strength of an argument, we compute a value for a set of arguments. The value $v_i(A)$ for an agent i for the argument set A is defined as follows:

$$v_i(A) = \frac{\sum_{a \in A} f_i(a) \times type(a)}{\sum_{a \in A} f_i(a)} \qquad (4)$$

with: $type(a) = \begin{cases} 1 & \text{si } a.T = + \\ -1 & \text{si } a.T = - \end{cases}$

As seen previously, the intention variable is calculated from the attitude, the subjective social norm and the PBC (see equation 1).

Agents estimate their attitude from their arguments using the following procedure:

1. Simplifying the argument graph $(\mathcal{A}, \mathcal{R})$ by removing mutual argument attacks with the following rule: delete each arc $(a, a') \in \mathcal{R} \wedge f_i(a') > f_i(a)$.
2. Compute the set of preferred extensions of the simplified argumentation graph.
3. Compute the attitude from the preferred extensions: evaluate the value of each extension using the equation 4. The extension retained is the one which absolute value is maximal.

We consider that the uncertainty on the attitude does not change during the simulation: it is specific to each agent but remains constant.

A first element which intervenes in the decision of the agents is their state of interest with regard to the innovation. The state of interest e_i of an agent i concerning the innovation is calculated from the intention of the agent I_i and its uncertainty on its intention u_i^I :

$$e_i = \begin{cases} yes & \text{if } I_i - u_i^I > 0 \\ no & \text{if } I_i + u_i^I < 0 \\ maybe & \text{otherwise} \end{cases} \qquad (5)$$

The decision state of an agent is determined according to the rules presented in Figure 1. These rules take into account the state of interest and the information attribute:

1. If an agent does not have enough information ($\neg informed$):
   – If the agent is not interested ($e_i = no$), then its decision state is that it is not concerned (*not concerned*). It no longer pays attention to information it might receive from outside potential adopters.

  - If it is interested ($e_i = yes$), then it enters the information seeking state (*information request*).
2. Once it has received enough arguments (*informed*):
  - If the agent is not completely interested ($e_i = no$ or $e_i = maybe$), it decides not to adopt the innovation (*no adoption*).
  - If the agent is interested ($e_i = yes$), then it will go to the pre-adoption state (*pre adoption*). This state corresponds to a period during which the agent thinks about its choice. The interactions it has with other agents can make it change its mind.
3. During the pre-adoption state (*pre adoption*), the agent continues to receive information:
  - If its interest remains positive during a given period of time, the agent will adopt the innovation and put it into practice (*adoption*).
  - If not, the agent will not adopt it.
4. The adoption state is the phase during which the agent puts the innovation into practice. The use of the innovation brings the agent a certain satisfaction which is measured during q time steps:
  - If its average satisfaction during this period is positive, it is defined as satisfied with the innovation (*satisfied*).
  - If not, it is dissatisfied with the innovation (*unsatisfied*).

Interactions between agents At each step of the simulation an agent can be influenced by another agent. This influence will be marked by two disjoint processes: the updating of the subjective norm and the exchange of arguments.

To come back to the first point, we consider that an agent interacting with another one will update its subjective norm, i.e. its perception concerning the adoption intention of its social network. The equation used for this is inspired by the work of [5] on social influence. Let agent i be influenced by agent j, its subjective norm $s_i(t+1)$ at simulation step $t+1$ will be calculated by :

$$s_i(t+1) = s_i(t) + \mu(1 - u_j^I)(I_j - s_i(t)) \tag{6}$$

Similarly, its uncertainty about its subjective norm, $u_j^s(t+1)$, will be computed by:

$$u_i^s(t+1) = u_i^s(t) + \mu(u_j^I - u_i^s(t)) \tag{7}$$

with:

  - μ: coefficient allowing to accentuate the influence of the others. Generally $\mu = 0.1$.

The second process corresponds to the direct influence of another agent through the exchange of arguments. As in most dynamic models of opinion, we consider that in order to exchange arguments, the agents must not be too dissimilar in terms of opinion.

The theory of planned behavior dissociates the subjective norm from the intention and the method used to compute the similarity between two agents i and j only takes into account the opinions of individuals (for us the intention).

Thus, when agent j interacts with (and thus tries to influence) agent i, the similarity between these individuals will be calculated from their intention and uncertainty. [5] propose a similarity calculation such as:

$$sim(i,j) = min(I_i + u_i^I, I_j + u_j^I) \qquad (8)$$
$$-max(I_i - u_i^I, I_j - u_j^I) \qquad (9)$$

with:

- I_i et u_i^I: the agent's intention i and its uncertainty.

If this similarity is greater than the uncertainty of agent j trying to influence agent i, then, j will be able to give an argument to agent i. The argument transmitted by j will depend on its decision and information state:

- An agent *not concerned* does not transmit an argument.
- An agent who is not satisfied with the innovation or who does not adopt it will transmit an argument against the innovation.
- An agent in *information search* can transmit an argument for or against the innovation. The type of argument is not taken into account because the agent is at the stage where it does not yet have a stable intention.
- An agent with a positive opinion, i.e. who is in the process of adopting, who adopts or who is satisfied with the innovation, will transmit a positive argument.

4   Application

4.1   Context

In the Louts region (South-West of France), mechanical meters, which belong to farmers, fail to estimate water consumption correctly because of their low accuracy. This is an advantage for the farmers, as there is less risk of being overcharged if the allocated quota is exceeded. For this reason, the Ministry of the Environment has required a periodic refurbishment of the metering system every 9 years. The institution in charge of managing water distribution in this area is counting on this regulation to install its new communicating meters. These new meters are more precise and allow to follow in real time the consumption of each farmer and thus to better manage the use of water.

However, the institution is having difficulty convincing farmers to install this device because they perceive it negatively. This obstacle is closely linked to the distrust that farmers have of the institution. A large part of the farmers believe that the new meter does not benefit them and that it is only useful for the institution. However, a minority, more inclined to new technologies, finds arguments in favor of these meters, such as the management of material leaks,

the automatic calculation of consumption to regulate at best the withdrawals in order not to exceed the allocated quota and to limit the losses.

The analysis of various scientific documents and websites has allowed us to identify thirty-five arguments (14 (40 %) against and 21 (60 %) in favour) divided according to five criteria: confidence (in the institution), ecology, social, productivity, financial.

We propose, based on these arguments, to study the changes of intention and adoption decision of the agents in relation to the communicating water meters. In particular, we propose to follow two indicators: the average intention of agents and the rate of adopters.

4.2   Parameterization of the model

The theory of planned behavior requires to define a certain number of parameters. To give values to these parameters, we used the psychological profiles defined by [9] which provides for each of these profiles the proportion of the profile as well as a mean and a standard deviation for the initial values of the TPB.

Concerning the other parameters, we used the following values:

- Number of agents: 60 (number of irrigating farmers of the Louts who subscribe to the pumping system).
- Social network: allocation of connected agents according to the Watts-Strogatz small world construction algorithm (with average node degree K =4 and probability of randomly "reconnecting" a social connection p =0.2).
- Adoption threshold: 0.56 [9]
- Number of simulation steps between adoption and satisfaction calculation (q): 15.
- Quantity of arguments for an agent to be considered as informed inf_{args}: 4.
- Maximum quantity of arguments per agent max_{args}: 7.
- Arguments initially known: a random number between 1 and max_{args} arguments drawn randomly in the set of arguments.
- Uncertainty on the attitude: draw according to a normal law $\mathcal{N}(\mu, \sigma^2)$ with μ and σ defined according to the agent's group.
- Subjective norm: draw according to a normal distribution $\mathcal{N}(\mu, \sigma^2)$ with μ and σ defined according to the agent's group. This value will evolve according to the interactions with other agents (equation 6).
- Uncertainty on the subjective social norm: drawing according to a normal distribution $\mathcal{N}(\mu, \sigma^2)$ with μ and σ defined according to the agent's group. This value will evolve according to the interactions with other agents (equation 7).
- Weight of the attitude in the intention: 0.229 [9].
- Weight of the subjective norm in the intention : 0.610 [9].
- Weight of the PBC in the intention: 0.161 [9].

The complete model and all the data and parameters used for the experiments are available on Githubt[5]. The model has been implemented using the GAMA platform [14] and in particular its plugin dedicated to argumentation [15].

4.3   Analysis of the stochasticity

In a first experiment, we analyze the impact of the stochasticity of the model on the results. The main objective is to find a threshold value of replications beyond which an increase in the number of replications would not imply a significant decrease in the difference between the results. To do this, we compare the average agent intention and adopter rate for different numbers of replications (from 0 to 500).

Figure 2 shows the standard deviation obtained for the 2 indicators. These results show that 100 replications are enough to have a standard deviation close to the limit. It is therefore not useful to go further.
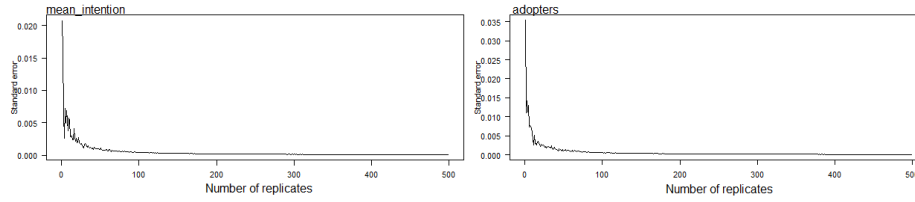

Fig. 2. Standard deviation of mean intention and adopter rate after 3000 simulation steps as a function of number of replications

4.4   Evolution of agent intention and number of adopters

Figure 3 presents the results in terms of the evolution of the average agent intention and adopter rate.

A first observation is a tendency towards a greater acceptance of communicating water meters with a final adoption rate higher than 0.7. It is interesting to note that similar phenomena were observed when mechanical water meters were introduced.

A second observation is that from the beginning of the simulation, the agents have a rather positive opinion on the communicating water meters (average intention higher than 0.2) leading, once the different stages defined by Rogers are passed, to a significant adoption of the technology. The average intention then tends to increase, first marking the influence of agents with a positive view of communicating water meters. In a second phase, this increase becomes almost zero, marking a phase where agents being more confident in their opinion and

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[5] https://github.com/LSADOU/Innovation-Argumentation-Diffusion

being more polarized in terms of intention, they tend to stop trying to convince agents with an intention very different from theirs.

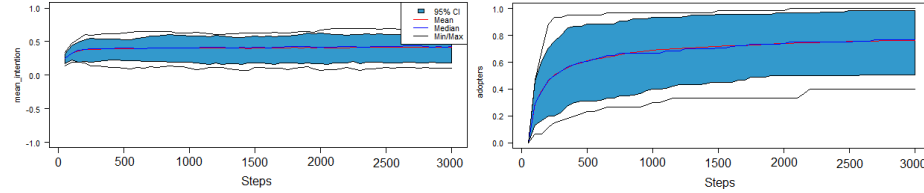A last important element is that the simulations tend to stabilize after 2500 simulation steps.

Fig. 3. Evolution of average intent and adopter rate for 3000 time steps (100 replications)

5   Conclusion

In this paper, we have proposed a model of innovation diffusion based on the theory of planned behavior and on the explicit representation of innovation information exchange through arguments. The model allows to take into account the heterogeneity of the actors by linking the information carried by the arguments and the agent's preferences (trust in information sources, preference criteria). We have also integrated an explicit description of the innovation adoption states and the dynamics of the resulting interactions.

An application of this generic model has been proposed for the issue of farmers' adoption of communicating water meters. The first experiments carried out illustrate the type of studies that can be conducted. To go further in this study, an important work will concern the data collection. Indeed, some of the parameters of the model used for the experiments were estimated or drawn at random. A future objective is to set up field surveys to obtain these parameters. Similarly, through questionnaires, we would like to obtain data on the evolution of farmers' opinions on communicating water meters in the Louts region, which would allow us to validate the results obtained by simulation.

Acknowledgements

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