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The role of emotions on communication and attitude dynamics: an agent-based approach

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Abstract. This paper presents a multi-agent model for simulating attitude formation and change based on individual’s affective response to the perception and communication of information. Individuals observe actions performed by social objects, they exchange beliefs about the actions depending on their narrative interest and compute attitude values toward the social objects. The affective response considers the emotional impact of the action for the participants and its unexpectedness. We illustrate, through several simulation experiments, the role of these affective components on attitude dynamics.

1 Introduction

How would a population react to information from a government or a company (ads) about *e.g.* any action, product, or innovation? This could be tackled through the concept of attitude dynamics. This notion of *attitude* derives from social psychology and could be defined as “a mental and neural state of readiness organized through experience, exerting a directive or dynamic influence upon the individual’s response to all objects and situations with which it is related” [2].

In this paper, we propose a multi-agent based simulation model that will help us to better comprehend attitudes dynamics. Our goal is to propose a model that articulates the cognitive and emotional dimensions of attitudes within a population. To do so, we consider agents that construct their attitudes through a rational process as proposed by Fazio [8], and we combine this with Dessalles’ approach of information interest as a basis for estimating the affective response. We illustrate our approach in the context of stabilization operations simulation: we study how so called “non-kinetic” actions (*i.e.* that do not rely on effective usage of force) alters population’s perception, attitudes and behaviors toward the UN Force.

The next section presents related works on attitude dynamics and on communication for attitude formation. Section 3 presents our agent model and the attitude dynamics. Section 4 presents a first validation of our model on concrete scenarios.

2 Related works

Attitude dynamics studies diverse complex social phenomena such as the vote, the expansion of extremism or the diffusion of information and could be studied along three different axes [16]: the representation model of attitude, the communication mechanism and the impact of the interaction network topology. In our work, we will focus on communication mechanism and the attitude model.

2.1 Communication mechanism

One dimension we consider in our research for attitude dynamics is the diffusion mechanism where actors influence each other. In most works, the exchanged information is the attitude's value itself [16, 4]. While it is true that daily communication is heavily based on attitudinal information (*e.g.* assessment without arguments, commercials *etc.*), conversational narratives (reporting facts) also represent a significant part of communication, maybe up to 40% according to Egging [7]. For this reason, we propose to base our attitude dynamics and communication mechanism on beliefs exchange and update rather than direct attitudinal influence. However, social and cognitive psychology have extensively worked on the topic of the interest of information in social communication (*e.g.* [9]). These works tend to define factors and mechanism that intervene in individual's selection of information that are worth to be retained or communicated. In this context, the Simplicity Theory proposed by Dessalles [6] seems to present a promising approach to fulfil this task. The main idea of this model is to define information's interest to be communicated or retained by an individual as a function of its emotional impact and unexpectedness level experienced by the individual. Integrating this theory in the communication protocol in our model would enable the agents to select the most convincing beliefs to communicate and also to retain. In this paper, agents will exchange beliefs and will select them according to the Simplicity Theory.

2.2 Attitude model

Attitude dynamics mostly depends on the representation model of attitude. The first models of attitudes (*e.g.* [11]) were based on binary or real values. During the last decade, several works proposed more complex representations of attitudes (*e.g.* [12]). However, as was pointed out by [4], most of these models' focus is limited to the interaction between individuals: they do not consider the construction mechanism of the attitude itself.

Other researches in social psychology study the formation of attitudes at an individual level (*e.g.* [13, 8]). In these models, attitudes are composed of three components: cognitive, affective and conative. The cognitive part is based on factual information (*e.g.* beliefs) concerning the social object. The affective dimension corresponds to the emotional response of the subject when he is confronted to the representation of the social object. The conative component refers to previous or intended behaviors that are related to the social object. However, this component is controversial due to its closeness to the cognitive part.

Urbig and Maltz [15] achieved to take into account the cognitive aspect in their model of attitude based on beliefs. Indeed, they proposed to represent attitudes as the sum of the evaluations of the object's features that can be seen as beliefs on the object. While this model constitutes an interesting view on attitude formation, it has two limits with respect to our objectives.

First, the attitude revision is based on the bounded confidence model (*e.g.* [5]): when two individuals have attitude values close to each other, agents converge their attitudes. As a consequence, the attitudes' values are no longer connected to the beliefs of each agents. However, Fazio's model [8] of attitude would enable to keep the attitude connected to its forming beliefs, as a set of memory associations between the object and its evaluations based on information concerning the object. Each of these evaluations is weighted by an accessibility value determining the evaluation's degree of reminiscence. By essence, this model maintains a balance between the cognitive representation of the object of the individual and its corresponding attitude.

Second, their attitude model does not embody an emotional component since it represents only the cognitive dimension. Indeed, the evaluation of features does not take into account the affective response to the information. The agents compute their attitudes in a purely rational way. Here again, the Simplicity Theory proposed by Dessalles [6] seems to present a promising approach to overcome this weakness. As mentioned above, this theory embodies an emotional component in the computation of the information's interest. Integrating this theory into the beliefs evaluation mechanism of the attitude formation would enable individuals to express their affective reaction.

Hence, we choose to base our attitude representation on the combination of Dessalles' Simplicity Theory and Fazio's attitude representation.

3 Model

3.1 General approach

Our model is based on the following principle: a simulation corresponds to the execution of actions (*e.g.* tax decrease, recall campaign of a product, attack etc.) by *actors* (*e.g.* a political party, a brand, policemen, terrorists or others) on a population. Individuals of the population communicate about these actions with the others and form an attitude toward the actors. In our model, we focus on the *interest* of an action, *i.e.* the tendency for individuals to remember it and to communicate about it.

In our model, we consider a set of actors A and a set of individuals Ind . For each $i \in Ind$ and $actor \in A$, we denote $att(i, actor) \in \mathbb{R}$ the attitude of the individual i toward the actor $actor$. Individuals are characterized by their social group (*e.g.* ethnic group) and are organized following a small-world communication network topology [10]. Concretely, each individual $i \in Ind$ is represented by a computational agent and is characterized by his neighbors in the communication network $Cnt(i) \subset Ind - \{i\}$ and a social group $sg(i) \in SG$ with SG the set of social groups. Each group has a static attitude toward the members of the other group, defined as $att(sg_1, sg_2)$.

As actors perform actions on the population, or communicate about such actions, individuals will build a representation of these actions, which forms their set of beliefs. Beliefs about actions will be the core element in our model: attitudes and communications will be based on these beliefs. We note $a(i)$ the belief of individual i about an action a . Each $a(i)$ is a tuple:

$$a(i) = \langle name(a), actor(a), bnf(a), payoff(a), date(a) \rangle$$

with:

- $name$ the unique name of the action
- $actor \in A$ the actor who performed the action
- $bnf \in Ind$ the beneficiary of the action, *i.e.* the individual which undergoes the action
- $payoff \in \mathbb{R}$ the impact value of the action, negative when the action is harmful (*e.g.* attack) and positive when it is beneficial (*e.g.* tax decrease)
- $date \in \mathbb{N}$ the occurrence date of the action.

We also compute $a_{perso}(a, i)$ the last occurrence of the action a on the individual i himself (*i.e.* $bnf(a) = i$), $nbOcc(a(i))$ the number of occurrences of the same action and $nbOcc_{SG}(a(i), sg)$ the number of occurrences per social group sg . For this computation, we consider two different $a(i)$ in the belief base to represent the “same action” if they have the same $name$, $actor$ and $bnf.sg$. These numbers of occurrences are considered from the agent’s point of view only.

3.2 Interest of an action

In order to determine what to base their attitude on and what to communicate to other individuals, agents estimate a model of interest of the actions in their belief base. The model of interest is based on the Simplicity Theory of Dessalles [6]. This theory proposes to define the *narrative interest* NI of an information according to the emotion E and the surprise level S it causes to the individual using the following formula:

$$NI(a) = 2^{E(a)+S(a)} \tag{1}$$

E corresponds to the emotional response intensity of the individual when faced to an information, in our model it is based on the payoff amplitude of an action’s impact. The surprise level S translates the sentiment of unexpectedness felt by the individual.

Emotional intensity The emotional intensity E corresponds to the emotional amplitude (non-zero) experienced by the individual when exposed to the event. Dessalles [6] shows that, when the stimulus impact is unbound, the emotional intensity follows a logarithmic law in conformity with Weber-Fechner’s law of the stimuli (in our case, the stimuli values correspond to the emotional intensity of an action through its payoff):

$$E(a) = \log \left(1 + \frac{|pyf(ip(a))|}{\xi} \right) \quad (2)$$

The parameter of sensibility $\xi \in [0, 1]$ modulates the emotional response’s intensity value.

Surprise Following Dessalles’ theory, the surprise experienced by an individual when exposed to an event derives from a level of raw unexpectedness U_{raw} (*e.g.* “It is surprising that a Taliban saves a citizen”). This level is reduced by a personal reference of unexpectedness U_{perso} based on a personal experience (*e.g.* “But I have once been saved by a Taliban before”):

$$S = U_{raw} - U_{perso} \quad (3)$$

In the Simplicity Theory, several dimensions are considered for the computation of surprise (*e.g.* geographical distance, recency *etc.*). In our model, we use two dimensions: the temporal distance and the social distance, which lead to four unexpected values: U_{raw}^{time} , U_{raw}^{social} , U_{perso}^{time} and U_{perso}^{social} . The following subsection presents the computation of these four elements.

In all four cases, the unexpectedness of the event (in our model, the action) can be defined by the contrast between its generation complexity and its description complexity: $U^x = C_w^x - C_d^x$ with x the dimension. The generation complexity C_w defines the level at which it could be anticipated by the individual based on its current knowledge base. The description complexity C_d must be understood in the meaning of Shannon’s information theory [14], *i.e.* the size of the smallest computational program that could generate this event.

Raw temporal distance (U_{raw}^{time}) The temporal complexity of generation refers to the probability that the action occurs at a given instant. This notion could be interpreted as the usual time gap between two occurrences of the action: the more the action is rare, the bigger the gap is, the less it is probable, the more it is unexpected.

Therefore we define the usual time gap using the difference between the occurrence date $date(a)$ of the action a and its last occurrence date $date(a_{old})$: $C_w^{time} = \log_2(date(a) - date(a_{old}))$. The temporal complexity of description corresponds simply to the elapsed time between the action and the current time t : $C_d^{time} = \log_2(t - date(a))$.

Thus, the unexpectedness level for the temporal dimension is obtained by:

$$U_{raw}^{time}(a) = \log_2(date(a) - date(a_{old})) - \log_2(t - date(a)) \quad (4)$$

Raw social distance (U_{raw}^{social}) The social complexity of generation refers to the probability that the action occurs on a beneficiary who belongs to a particular social group (*e.g.* “It is rare that Pashtuns are victims of a Taliban attack”). We define it with $C_w^{social} = -\log_2\left(\frac{nbOcc_{SG}(a,sg(i))}{nbOcc(a)}\right)$ with $nbOcc_{SG}(a,sg(i))$ the occurrence number of the action a whose beneficiary is a member of the same social group $sg(i)$ as the agent.

The description complexity C_d^{social} corresponding to the social distance between the individual and the beneficiary of the action depends on two factors: the distance in the social graph and the average degree in the graph. Indeed, the higher the degree, the more complex it will be to describe a single step in the graph (in terms of information theory) and this influence is linear. However, the distance in the graph has an exponential impact on the social distance generation (since it requires to describe all possibilities at each node). Thus, $C_d^{social} = \log_2(v^d)$ with v the degree of the graph and d the shortest distance between i and $bnf(a(i))$ in the graph.

Hence we obtain the following formula:

$$U_{raw}^{social}(a) = -\log_2\left(\frac{nbOcc_{SG}(a,sg(i))}{nbOcc(a)}\right) - \log_2(v^d) \quad (5)$$

Personal temporal distance and personal social distance The personal unexpectedness is based on the last occurrence of the action a which has personally affected the individual, *i.e.* the last occurrence of the action (with the same *name* and *actor*) for which $bnf(a)$ is the agent i itself. We denote a_{perso} this particular occurrence.

The computation of the unexpectedness values is the same as above, except that the search of experienced occurrences in the belief base is limited to actions with i as the beneficiary:

$$U_{perso}^{time}(a) = \log_2(date(a) - date(a_{perso})) - \log_2(t - date(a)) \quad (6)$$

$$U_{perso}^{social}(a) = -\log_2\left(\frac{nbOcc_{SG}(a_{perso},i)}{nbOcc(a)}\right) \quad (7)$$

where $date(a_{perso})$ denotes the date of the last time the action happened to the subject, and $nbOcc_{SG}(a_{perso},i)$ the number of occurrences for this action. In the case where the individual has never personally experienced the action, his personal unexpectedness is nil, $U_{perso} = 0$.

Subjective narrative interest In order to take into account the attitude of the individual i toward the action’s beneficiary, we propose to weight the narrative interest NI by the absolute value of his attitude. Indeed, the more the attitude toward the beneficiary is high, the more the interest of communicating it increases:

$$SNI(a,i) = |att(i,a.subj)| \times NI \quad (8)$$

3.3 Communication

In our model, actions can be perceived via direct perception (the agent is beneficiary of the action), actor’s communication toward the population (the agent receives a message from the actors) or intra-population communication (the agent receives a message from another individual). While the first two cases are scripted in the scenario, the intra-population communication is based on the list of contacts of the agent ($Cnt(i)$) and the subjective interest of the action $SNI(a(i))$.

At each time step of the simulation, the agent considers all actions perceived at this step. It performs a probabilistic selection of some actions, based on their subjective interest, and distributes messages about the selected actions randomly to its contacts.

Let $sni_{max}(t)$ be the maximum sni for actions received at this time step. For each action a and for each contact j , the probability that agent i sends a message about a to j is $p_{sending}(a) = \frac{SNI(a)}{sni_{max}}$.

3.4 Attitude computation

When the agent receives a new information about an action a , it adds it to its belief base (if the action is not already present) and, possibly, communicates about it. Moreover, the agent revises its attitude toward the actor of the action.

Our model of attitude construction is based on the model proposed by Fazio [8] (see section 2.2) as in [3]. In our case, the accessibility of an action is the subjective narrative interest $SNI(a(i))$ since the retention interest and the narrative interest are equivalent in cognitive psychology. Also, the benefit is the action payoff weighted by the attitude toward its beneficiary (as proposed by Fishbein and Ajzen [1]):

$$benefit(a) = payoff(a) \times att(i, bnf(a)) \quad (9)$$

Let $aList(i, actor)$ be the list containing the actions performed by the actor in the belief base of agent i . The attitude $att(i, actor)$ of the individual i toward the $actor$ is given at each time of the simulation by:

$$att(i, actor) = \sum_{a(i) \in aList(i, actor)} \left(\frac{benefit(a) \times SNI(a, i)}{|aList(i, actor)|} \right) \quad (10)$$

4 Simulation results

This section presents two experimental studies of our model to analyze the impact of some key parameters on the attitude dynamics in the context of a stabilization operation. First we evaluate separately the impact of emotion E versus surprise in the narrative interest NI (4.2). Second, we consider the impact of social groups by comparing two different scenarios. Beforehand let us describe the experimental settings.

4.1 Simulation settings

All experiments are based on a set of shared parameters settings:

Population: The population is split into three social groups (ethnic group A, B and C) each composed of 33 individuals connected by an interaction network based on a small-world topology. In the first experiment, there is no inter-group attitude (the population behaves as a single social group). In the second experiment, we introduce inter-social group attitudes. We denote the attitude of the individual i belonging to the social group SG_X toward the individual j belonging to SG_Y $att(i, j) = sgAtt(X, Y)$. These static attitudes are defined as follows: $sgAtt(A, B)=0.8$; $sgAtt(A, C)=-0.5$; $sgAtt(B, C)=-0.2$ (*i.e.* social groups A and B are allied against a third group C).

Actor: Only one actor representing the Blue Force (*e.g.* UN) is sufficient for our experimental needs. The initial attitudes of all individuals toward this actor is set to zero.

Scenario: People are confronted to a series of actions with a *payoff* = 1 performed by the actor every 5 time steps (*e.g.* the UN brings food and medic once every two days). In the first experiment all the social groups are affected evenly (random selection on the whole population). In the second experiment we will compare two alternative scenarios: in the first version (called $S1$) the actor affects only random individuals of social group A ; in version $S2$, three phases will affect in order the social group SG_A , SG_B and finally SG_C . Each phase last 30 ticks and affects random people of the corresponding social group. The total amount of action that occurs remains the same across the two scenarios.

Default parameter: ξ is set to 1. In this paper we do not study the sensibility of the model to ξ .

4.2 Analysis of narrative interest components' impacts

The narrative interest is composed of two key components (see section 3.2): the emotional impact E and the surprise S . To analyze the impact of these components on the attitude dynamics, we introduce α and we change the definition of NI into: $NI = 2^{E+\alpha \times S}$. Varying α comes to modify the balance between the emotional intensity and the surprise factors in the narrative interest. The smaller is α , the more emotional and the less surprised will be the agents. When α is very small, the agents tend to ignore the impact of past occurrences of the actions to compute their attitudes. In the case where $\alpha = 0$, the agents will base their attitude only on the emotional impact of the action's occurrences which remains static. Therefore, their attitudes reach the top value and remain stable once all agents have been aware of the information (see figure 1a). The figures 1 show the evolution of attitudes dynamics with α ranging from 0 to 1. Since the communication mechanism is stochastic, each presented result corresponds

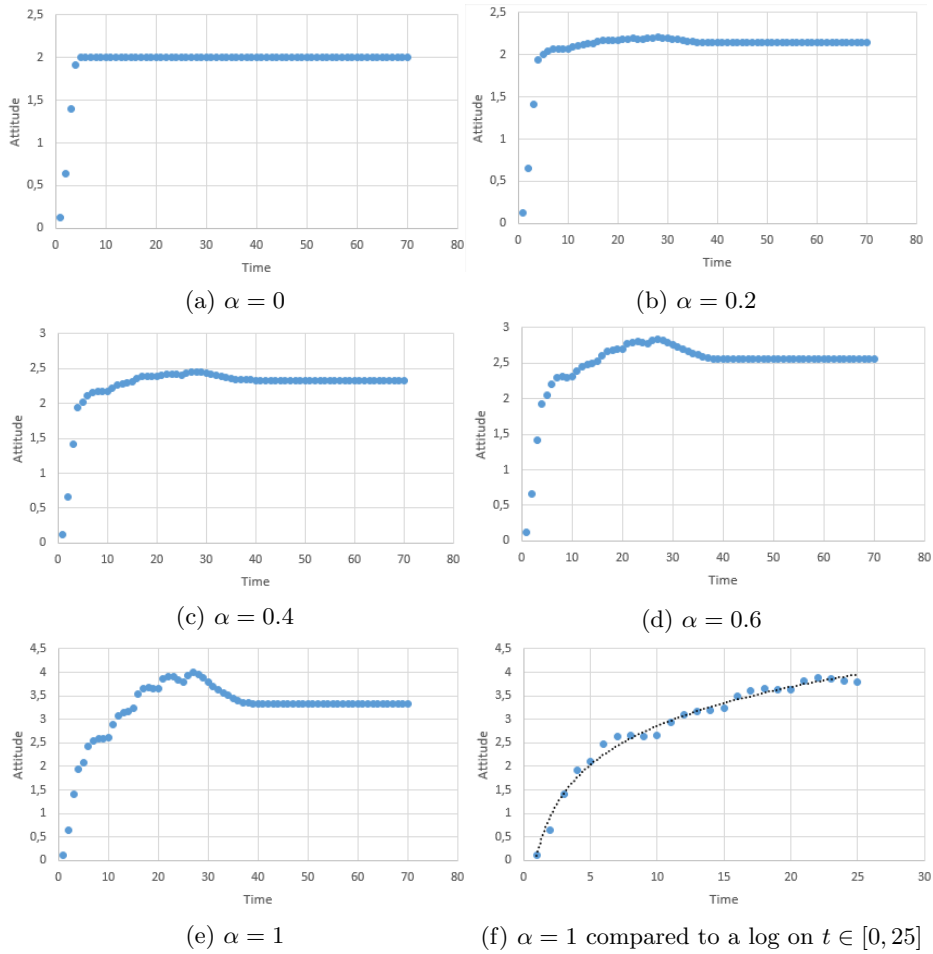


Fig. 1: Mean of attitudes in $S1$ with a varying α

to a mean curve obtained over a hundred simulation runs. We can notice three phenomena:

- The attitude value is boosted with the surprise factor: with α growing, the mean of attitudes reaches a higher value. This was predictable since the surprise factor is added to the accessibility of beliefs: its effect results in increasing the attitude value. Moreover, the figure 1f shows that the attitudes' mean increases following a logarithmic law between 0 and 30. This shape is due to the logarithmic components of the surprise.
- Habituation effect: in all simulations, the attitudes decrease after $t \simeq 30$. The repeated perception of the action's occurrences are no more beneficial for the actor since additional occurrences only affects negatively the attitudes. This effect is due to the growing number of people directly affected by the

occurrences. Thus they reduce their surprise using their personal occurrences (see equation 3).

- The mean value reaches a plateau: when $t > 40$, the attitudes’ mean remains stable. This stationary state is due to the fact that all the agents have experienced personally the action and also to the fact that the time period between occurrences is stable: the values of both time distance and social distance surprises have reached a threshold value among the whole population.

In further experiments, we analyzed the effect of $\alpha > 1$ and discovered that it has only an impact on the scaling: the shape of the attitudes means’ curves remain unchanged while the scale increases. Therefore, we will use $\alpha = 1$ in the following simulations.

4.3 The impact of social groups

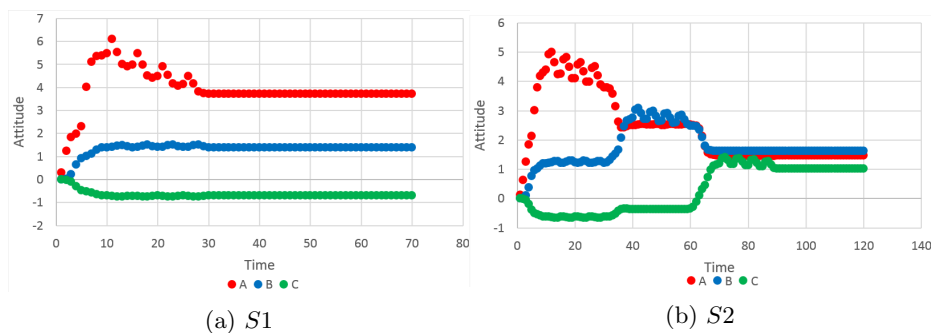


Fig. 2: Scenario comparison

In our model, agents are sensible to the beneficiary’s social group, and their attitude toward this group. To understand the sensibility to this factor, we propose to compare the two scenarios $S1$ and $S2$ presented above with the inter-social group attitudes.

Conflicts Figures 2 show the evolution of attitude means per social group in the two scenarios. We can notice that the attitudes of social groups vary in a conflicting manner. At the beginning of both scenario, SG_A being affected positively, its attitude towards the actor increases as explained in section 4.2. Besides, we can notice that SG_B and SG_C ’s attitudes are also affected despite that these social groups are not directly affected by the action’s occurrences. This is due to the intra-population communication that makes them aware of the ongoing actions on SG_A . Along time, more and more individuals come to know the actions, therefore impacting their attitudes. We can notice that the evolution of attitudes of SG_B and SG_C are opposite. This can be explained by

their different inter-group attitudes toward SG_A as presented in section 4.1: the evaluation of beneficial actions on SG_A is positive for its ally SG_B and negative for its enemy SG_C . Since SG_B is allied to SG_A , its attitude toward the actor follows SG_A due to the positive evaluation of the action’s benefit (see equation 9). Conversely, SG_C being the enemy of SG_A , the action’s benefit is evaluated negatively, thus leading to a negative attitude. This phenomenon is also visible on the three phases of the $S2$ (figure 2b).

Agreement While the three social groups have very different attitudes at the end of $S1$ (figure 2a) as it was predictable since only SG_A is positively impacted, they seem to reach a consensus in the scenario $S2$. Indeed, the figure 2b shows that despite conflicting evolutions among groups, they converge to 1.5 since they are equitably affected. However, we can notice that the final attitude values of SG_A and SG_B are very close as they are allied while the “enemy” SG_C is apart with a lower attitude.

5 Conclusion

We proposed a simulation model of attitude dynamics based on socio psychological theories. This model introduces an affective component in the formation of attitude and the diffusion of beliefs through the concept of information’s interest which embodies an emotional and an unexpectedness components. Moreover, the introduction of the Simplicity Theory enabled us to only have two parameters : ξ and α .

We studied the dynamics of this model on several examples that illustrate the impact of these cognitive components and the inter-social conflicts on the attitudes toward an external protagonist. The first experiment especially showed that repeated actions impacts are not linear. At the beginning, people accentuate their attitudes due to the surprise factor but, after a while, the evaluation is reduced due to an habituation effect. The second experiment presented the impact of having conflicting social groups on the general attitudes dynamics. In particular, we showed that despite diverging evolutions of attitude, when the groups are equitably affected, they tend to reach a consensus. Yet the validation of the socio-cognitive model is a challenging issue. In future works⁴, we intend to conduct deeper analysis the sensitivity of the model and also calibrate it using real world data such as opinion polls and action sequences of individuals. Furthermore, we would like to add a behavioral component to enable population agents to express their attitudes through actions.

⁴ Note that our model is not limited to military applications and can be applied to civilian use: the actors can represent any kind of active social object such as political parties, institutions, companies or brands

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