A computational model of social attitude effects on the nonverbal behavior for a relational agent

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Abstract:
The relations we have with others influence in a very subtle way our body gestures. These are cues that are used in an interaction in an unconscious process to communicate and understand an attitude. Depending on the gestures and facial signals one is displaying, a social attitude can be perceived. In this paper, we propose to model socio-emotional agents and how they can express such an attitude in a dyadic interaction. The focus will be on generating the nonverbal behavior of the virtual agent given the social attitude it wants to convey. Depending on the nature of the relation an agent has with someone else, its role and desires, it should display a different attitude and therefore it should display different nonverbal behaviors. In this paper, we propose a computational model based on the findings in Human and Social Sciences on the correspondence between social attitudes and nonverbal behaviors. This computational model is used to select the proper behavior of an agent during an interaction depending on the social attitudes it wants to convey and depending on its gender.

Keywords: virtual agent, relational agent, social attitude, nonverbal behavior

1 Introduction

Embodied conversational agents are used to endow different roles during interactions with users, for instance teachers [32], assistants, guides, coach [7], ally or enemy in video games [22]. In this different roles, agents must be able to express different social attitudes to enhance their believability.

The believability of an agent can be defined as the ability to provide an illusion of life [1]. Different kind of work has been done to increase the believability of agents. It is a difficult task as by doing so we may encounter the uncanny valley phenomenon [28], where we loose all believability of the virtual agent. The first idea is to make a more human-like appearance but we can also create a more human-like behavior. Some looked into how emotions could be conveyed by a virtual agent in order to increase its believability [1]. Starting from this idea, we aim at going a step further by designing agents capable of creating a social relation with users. Relational agents have been demonstrated many times to increase the engagement of the users in the interaction [11]. The model we propose makes the agent able to express different *social attitudes*. For instance, If a virtual agent wants one of its subordinate to do a work which he is not doing, the agent may express a dominant attitude to convey the message. The particular point we focus on, is the expression of these social attitudes through nonverbal behaviors. This paper is organized as follows. In the first section, we present the theories from the literature of psychology that illustrate the influence of social attitude on nonverbal behaviors. Then, in Section 3 we introduce previous research that has been done on relational agents. In Section 4, we present our computational model. Finally, we discuss in Section 5 the limits of our model and the perspectives of our research.

2 Theoretical background

The proposed model is based on studies in Human and Social Sciences that have explored the influence of nonverbal behaviors on social attitude's perception. Social attitude or interpersonal stance is an affective style that can be naturally or strategically employed in an interaction with a person or a group of persons. It consists of conveying a particular feeling in the interaction. For instance being friendly, dominant, hostile or polite [33]. Several studies describe how social relations are perceived through the nonverbal cues. Some studies [13, 20] represent social attitude with two dimensions: a *dominance* dimension (also called *power*, *control* or *agency*) that represents the degree of control one has on another, and a *liking* dimension also called *appreciation*, *affiliation* or *communion*), that represents the degree of appreciation, liking of another. In other studies [9] these dimensions are used among other dimensions like *formality* or *trust*. Dominance and liking correspond to the dimensions of the *Interpersonal Circumplex*, illustrated Figure 1. In [18], Gurtman presents this tool widely used in the social psychology field to describe interpersonal relations.
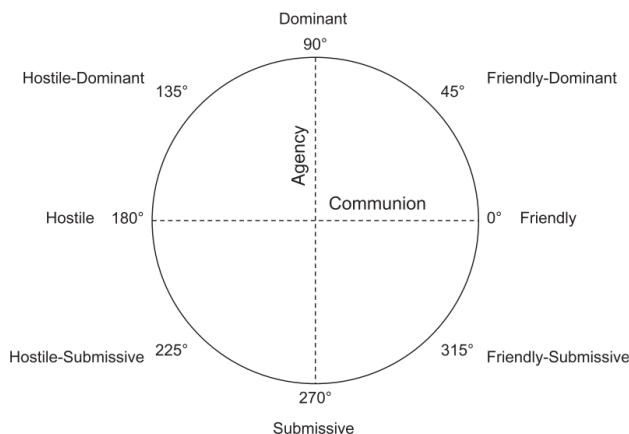
Figure 1: A generic interpersonal circumplex [18]

This tool describes interpersonal relations with the two axes *dominance* and *liking*.

Several studies have explored the expressions of dominance and liking through nonverbal behavior [8, 9, 10, 13, 20, 21, 24, 34]. Moreover some works have highlighted the influence of the gender of the interactants on one's nonverbal behavior [8, 21]. From this literature, we built a table of influence of the social attitudes and of the gender on the nonverbal behavior. We describe this table in Section 2. This table is used in the proposed computational model described in Section 4 to modulate the nonverbal behavior of an agent. Before presenting in details the model we introduce in the next section related works on relational agents.

3 Related Work

One of the challenges of the research in virtual agent is to increase their believability to enhance the human-machine interaction. For this purpose, the capacity to express nonverbal behaviors through different modalities is a key element [15]. In the following section, we present multimodal virtual agents. Few research seem to be done on agents able to express social attitudes. In section 3.2 we present some existing relational agents.

3.1 Multimodal Agents

Max is an example of a multimodal virtual agent able to express emotions through its facial expressions, its gestures and its verbal behaviors[2]. *Rea* [14] is a virtual agent

equipped with conversational functions. *Rea* can change her gaze or body posture, interpret those from the user and manage a conversation. Moreover, *Rea* is paying attention to the verbal cues but also to the non-verbal cues. It replies with speech and gestures in order to provide the same kind of nonverbal behaviors to the user. *Greta* [29] is a virtual agent based on SAIBA [25] for the general architecture and the MPEG4 standards [31] for generating the animation parameters. It has previously been integrated into the SEMAINE platform where it was able to show signs of understanding and reply to an user during a conversation [4]. Another framework is *MARC*, also using MPEG-4 standard and BML for the animation of its virtual agents. In [16], *MARC* has been used for displaying appropriate emotions during a game of Reversi against a user.

The presented multimodal agents have a non-verbal behavior that is computed based on communicative intentions and emotions. However, these agents do not consider the influence of the social attitude in their behaviors. Regarding influence on nonverbal behavior, Mancini and Pelachaud have proposed a framework that enables one to describe tendencies for a virtual agent in nonverbal behaviors expression [27]. These tendencies have an influence on the generated nonverbal behaviors and more precisely, they change their expressivity parameters. These parameters are the following[19]:

– *overall activation*: the quantity of movements;

– *spatial extent*: the amplitude of movements;

– *temporal*: the duration of the movements;

– *fluidity*: the continuity of movements;

– *power*: the dynamic of the movements;

– *repetition*: tendency to repeat specific movements;

The influence on the expressivity parameters is described in what they call a *Baseline*, composed of initial values for each parameter, and also in *Dynamic Qualifiers* that specify how these parameters are dynamically affected depending on the emotional state of the agent. One limit of this model is the lack of definition for the expressivity parameters according to the social context. In our model, we propose to go one step further by defining the influence of so-

cial attitudes of certain expressivity parameters. Indeed some works [10, 13] have shown that the social attitude impacts the spatial extend of one's gestures and one's quantity of movement.

3.2 Relational Agents

The influence of social relation means that an agent may not act the same with different persons based on the relation it has with each person. This can be through its actions but it can also be more subtle and be displayed in its nonverbal behavior. This can be very effective to increase the believability of the agent [22, 7]. Usually, an agent is talking and acting the same way with every user. Some research attempts to propose agents that convey different social attitudes during interactions.

Memory can be used to simulate a social bond, for instance in the conversational agent *May* [12]. *May* is reminding the user with previous topic they had. The study shows that the user felt a better connection with the agent because of the shared common ground. Tinker is a virtual museum guide that creates relationships with the visitors [6] by remembering them and recalling past interactions. It can also show empathy and use an appropriate nonverbal behavior to convey it. *Laura* is one of the first relational agents [7]. It displays different nonverbal behavior depending on the state of the relation it has with the user. It expresses different attitudes as the relation is evolving. Actually, Laura is only following the duration of the relation. The more a user interacts with it, the more it will express signs of closeness, no matter what kind of attitude the user has with it. *Rea* was also used in an experiment to make the user trust the agent [5]. It was using a planned dialogue, where small talk was used to gain user's trust and then it could talk about more serious topic after. *Eva* [23] uses the relationships it has with a user, built from the previous interactions, to generate different emotional response, verbal and nonverbal. Its interpersonal relations are also affected by the type of emotion triggered by the interlocutor. In [30], a computational model of the impact of emotions on social relations is also proposed. The virtual agent *Alfred* is able to convey different degrees of dominance by varying its gaze, facial posture and linguistic behaviors [3].

Our model aims at adding to an agent the ability to express different social attitudes. We propose to modulate the selected behavior of the agent depending on its social attitude. Indeed, in our model, the social attitude will inhibit or emphasize some of the agent nonverbal behaviors based on the results from the Human and Social Sciences.

4 Model

4.1 Theoretical Model

Based on the literature in Human and Social Sciences [8, 9, 10, 13, 20, 21, 24, 34] and in virtual agent[3, 7, 22], we have designed a table showing the influence of dominance and liking on the nonverbal behavior depending on the gender of the speaker (Table 1).

This table indicates the influence (inhibition characterized by a $\searrow$ and accentuation characterized by a $\nearrow$) of the dominance and liking on certain nonverbal behaviors. An empty cell means that the dimension considered does not have a significant influence. For instance, in Table 1, 4th row and 3rd column, this cell indicates that a dominant male person tends to have broad gestures. This table is used in the computational model to determine the influence of the social attitude on the nonverbal behavior. We present in more details this model in the next section.

4.2 Computational Model of Social Attitude Influence

In this section, we present a computational model that allows an agent to display, through its nonverbal behavior, the appropriate social attitude it wants to convey to its interlocutor. Our model modulates the probability to perform a specific nonverbal expression and also how it is expressed.

To modulate the expressivity of nonverbal behaviors, we use a similar approach as the work of Mancini and Pelachaud on dynamic behaviors [27]. In our model, we are using the table of influence (Table 1), to change the expressivity parameters of any agent given the social attitude it wants to convey. The functions that modulate the expressivity parameters are described more precisely in Section 4.4.

The social attitude. The virtual agent is characterized both by a *social relation* it has with its interlocutor and a *social attitude* it expresses during the interaction. The social attitude can convey the expressions of a social relation. However, one may decide to express an attitude different from the relation one has depending on

0	1	2	3	4	5	6
1		Nonverbal Behaviors	Dominance		Liking		References
2			♂	♀	♂	♀	
3	Hand movement	Initiates Hand Shaking	↗	↗			[13]
4	Gesture parameters	Has Broad gestures	↗	↗			[13]
5		High number of gestures	↗	↗	↗		[10, 13]
6	Touch Gestures	Touches other	↗	↗	↗		[9, 13, 22, 34]
7		Self-touches (hands)	↘	↘			[8, 13]
8		Self-touches (head)	↘	↘			[8, 13]
9		Object-Adaptors	↘	↘	↘	↘	[10]
10	Head Movement	Tilts head up	↗	↗	↗	↗	[10, 13]
11		Orients head toward other	↗	↗	↗	↗	[10, 13]
12		Shakes head	↗	↗			[13]
13	Posture	Has Erect posture	↗	↗			[13]
14		Leans forward toward other	↗	↗	↗	↗	[9, 10, 13, 22, 34]
15		Open body position	↗	↗	↗	↗	[9, 13, 22, 34]
16		Orients body toward other	↗	↗	↗	↗	[9, 10, 13, 22, 34]
17	Gaze	Pays attention to other	↘	↘	↗	↗	[9, 13, 22, 34]
18		Glares	↗	↗			[9, 13, 22, 34]
19		Engages in mutual gaze	↗	↗	↗	↗	[9, 13, 22, 34]
20		Gazes for a long time	↗	↗	↘	↘	[9, 13, 22, 34]
21		Averts gaze	↘	↘	↘	↘	[13, 10, 8]
22		Looks while speaking	↗	↗			[13]
23	Face	Expressing face	↗	↗	↗	↗	[13, 10]
24		Self-assured expression	↗	↗		↘	[13, 21]
25		Shows facial fear	↘			↗	[13, 21]
26		Shows facial sadness	↘	↘			[21]
27		Shows facial disgust	↗	↗		↘	[13, 21]
28		Shows facial anger	↗	↘			[13, 21]
29		Smiles				↗	[8, 9, 21, 22, 34]

Table 1: Table of influence of social attitude on nonverbal behaviors

one's goals or one's role. In our model, we focus more particularly on the social attitude. As a first step, we consider that the social attitude the agent wants to express is the exact representation of the social relation it has with the interlocutor. We suppose that the social attitude the agent wants to convey is an input of our model. We propose a model to generate the nonverbal behavior associated to this social attitude. As shown in Section 2, the social attitude influences one's nonverbal behavior. The social attitude may inhibit or emphasize some particular signals [13]. To represent the social attitude, we are using the interpersonal circumplex. Consequently, we consider the two following dimensions: *dominance* and *liking*. We represent formally the social attitude as follows:

Let $A_i(t)$ be the social attitude the agent wants to convey to an interlocutor i at a time t. We define $A_i(t)$ as the pair dominance $D_{A_i}(t)$ and liking $L_{A_i}(t)$ where both $D_{A_i}(t)$ and $L_{A_i}(t)$ take values in the interval $[-1, 1]$.

$$A_i(t) = (D_{A_i}(t), L_{A_i}(t))$$

The more the agent expresses dominance towards another agent i, the closer to 1 is the value of $D_{A_i}(t)$. The more an agent expresses liking towards another person i, the closer to 1 is the value of $L_{A_i}(t)$. When dominance and liking are equal to 0, it means that the agent expresses a neutral attitude. If the value of dominance (resp. liking) is below 0, the agent has a submissive

(resp. hostile) social attitude. In other words, the attitude is a point in *dominance × liking* space [1].

Architecture. We have integrated our model in the context of a SAIBA-like agent [25]. The SAIBA architecture defines three main components. The *Intent Planner* generates the communicative intentions (what the agent intents to communicate). For instance, a communicative intention can be the expression of joy. The *Behavior Planner* transforms these communicative intentions into a set of signals. A signal is a behavior expressed through a modality (e.g. speech, gestures, facial expressions). Multimodal expression (expressing and synchronizing signals on different modalities) is handled by this *Behavior Planner*. For the purpose of our research, we are using an extended version of a SAIBA architecture where signals are also endowed with the expressivity parameters described in section 3.1. Finally the *Behavior Realizer* outputs for each of these signals the animation parameters.
In our architecture, we add three modules to the SAIBA-like agent: the *Social Intention Filter*, the *Adaptor Generator* and the *Social Expressivity Modulator*. The resulting architecture is illustrated in Figure 2. Each component takes as input the social attitude of the agent, its gender and the table of influence. The *Social Intention Filter* take as inputs the potential signals (signals that might be selected to express the communicative intention) and outputs, for each signal that has a corresponding row in the table 1, a new probability to be expressed. The *Adaptor Generator* inserts new signals in the list of signals to be expressed. The *Social Expressivity Modulator* takes as input the list of signals to be expressed and assigns new expressivity parameters to each signals. These modules and their integration in the SAIBA architecture are described in details in the following.

The *Intent Planner* sends the communicative intentions to the *Social Intention Filter* instead of the *Behavior Planner* directly. For each communicative intention, a list of potential signals are available in a behavior set B. To each signal is associated a probability p_{signal} to be performed in order for the behavior planner to decide which signal will be executed. Indeed a communicative intention may be expressed through different signals. For instance, the agent wants to greet. A first possibility is to wave

with the arm and the hand and an alternative one could be just a head nod. The *Social Intention Filter* modifies the probability to express a signal depending on the social attitude of the agent. The *Behavior Planner* uses the probability p_{signal} to choose the appropriate signal to generate. In the next section, we describe in details the *Social Intention Filter* and the *Adaptor Generator*.

4.3 The Social Intention Filter and the Adaptor Generator

In our model, we propose to modify the behavior set (both the list of signals and the probability associated) depending on the social attitude and the gender of the agent. To compute the probability of the signals, we define a function g.
For each signal s of B, we search in the table 1 for a corresponding row. If one is found, we represent it in a dominance × liking space, depending on the gender of the agent. Indeed, we consider $\nearrow$ and $\searrow$ from Table 1 respectively as 1 and -1. An empty cell is considered as 0. This representation in the dominance × liking space is noted P_s.

$$P_s = (D_{P_s}, L_{P_s})$$

The function g uses an Euclidean distance between P_s and $A_i(t)$ (the current social attitude of the agent). We have choosen the Euclidean distance since our objective is to compute the impact of the agent's social attitude (described in a two-dimension space) based on the difference between the current agent's social attitude and the extracted representation from Table 1. Note that other functions could be used like the Manhattan distance. Let d be the mathematical function calculating the Euclidean distance.

$$d(P_s, A_i(t)) = \sqrt{(D_{P_s} - D_{A_i}(t))^2 + (L_{P_s} - L_{A_i}(t))^2}$$

The higher the distance is, the lower the influence is for this signal. The influence is proportional to $1 - d$. The new probability of the signal corresponds to the mean between the resulting value of $1 - d$ and the original probability p_{signal}.

$$g(P_s, A_i(t), p_{signal}) = \tfrac{1}{2}(1 - \tfrac{d(P_s, A_i(t))}{2\sqrt{2}} + p_{signal})$$

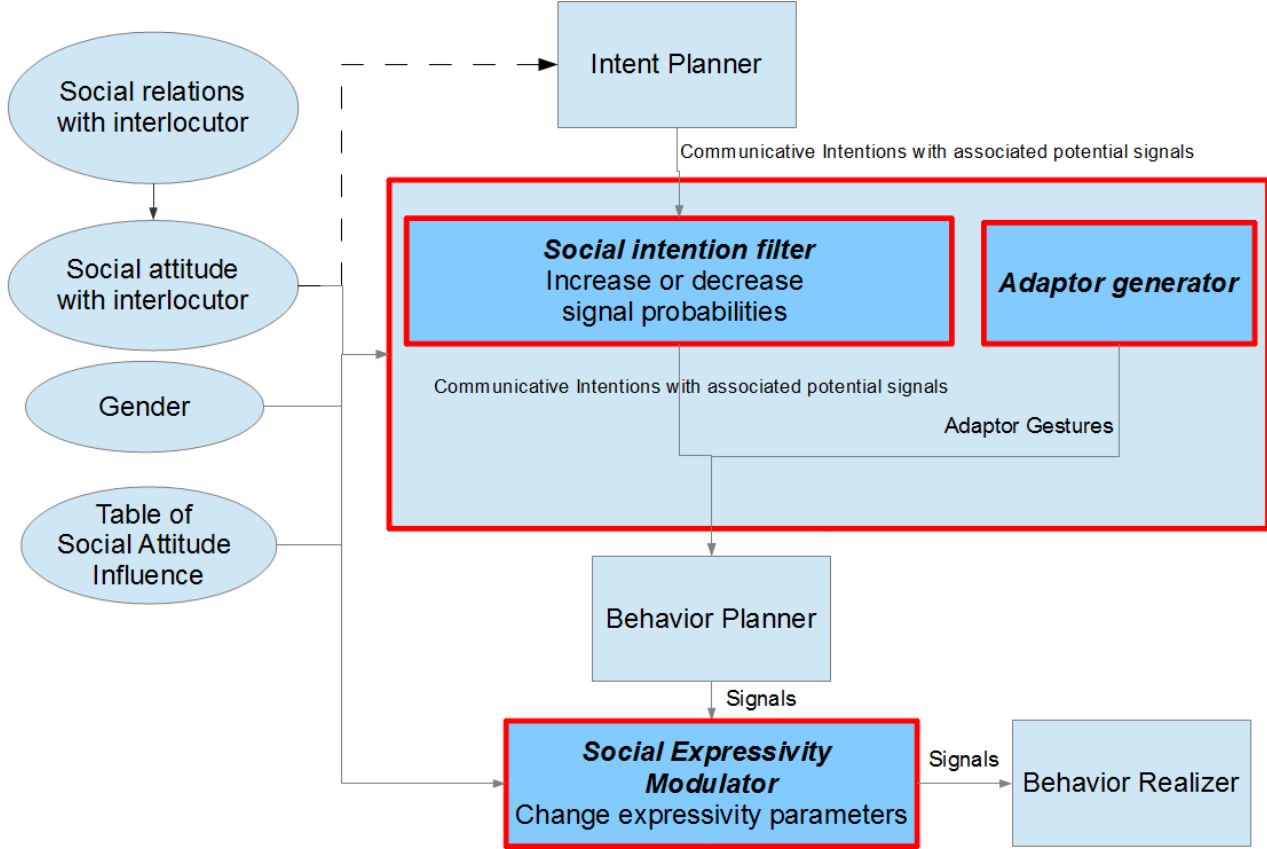1. For now, we are not defining yet how social attitude are evolving through time

Figure 2: Social Attitude Influence Model

This function returns a value in the interval $[0, 1]$.

The probability of a signal is then computed based on the original probability of the signal, its current social attitude $A_i(t)$, the gender G of the agent and the proposed table of social attitude's influence (Table 1). Let's introduce an example to illustrate the proposed function g. Let's consider a male agent with the communicative intention to express sadness. The social signal has already a probability p_{signal}. The table gives us the point $P_{FSadness}$ of coordinates $(-1, 0)$ (26th row, 3rd and 5th columns of Table 1). The more the agent wants to communicate a dominant attitude, the higher the distance between $P_{FSadness}$ and its attitude $A_i(t)$ is, and the lower the computed output probability is.

The social attitude may lead someone to express specific gestures, for instance, self-touches, or object-touches. these gestures are called adaptor gestures [17]. In our model, we give the capability to an agent to generate new adaptor gestures depending on its social atti-

tude. These adaptor gestures are selected based on Table 1. They correspond to the nonverbal behaviors *self-touches (hands)*, *self-touches (face and head)* and *object-touches*. In the proposed architecture Figure 2, the *adaptor generator* generates the new adaptor gestures in the list of signals to be expressed.

Finally, the *Behavior Planner* module generates a set of gestures to perform depending on the communicative intentions and the probabilities of the associated signals. Then, this set is transferred to the *Social Expressivity Modulator*, instead of the *Behavior Realizer*.

4.4 The Social Expressivity Modulator

The *Social Expressivity Modulator* changes the expressivity parameters of the gestures according to Table 1 to reflect the agent's social attitude. Given Table 1, we consider two expressivity parameters [2]: the *overall activation* parameter and the *spatial* parameter (4th and 5th rows of

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2. However, other parameters may be impacted as well by the social attitude. A deeper study in the future will enable us to extend this model

Table 1). The expressive parameters take their values in the interval $[0, 1]$.

Let SPC be the mathematical function that computes the *spatial* expressivity parameter from Table 1 and the current attitude $A_i(t)$ of the agent. This function will return a value in the interval $[0, 1]$.

$$SPC(D_{A_i}(t), L_{A_i}(t)) = 1 - \frac{d(P_{BroadGesture}, A_i(t))}{2\sqrt{2}}$$

Let OVA be the mathematical function that computes the *overall activation* expressivity parameter from Table 1 and the current attitude A_i of the agent. This function will return a value in the interval $[0, 1]$.

$$OVA(D_{A_i}(t), L_{A_i}(t)) = 1 - \frac{d(P_{NumberGestures}, A_i(t))}{2\sqrt{2}}$$

These functions are also based on Euclidean distance. If the agent is very dominant, the lower the distance between $P_{BroadGesture}$ (resp. $P_{NumberGestures}$) is, the higher the result of SPC (resp. OVA) is. The obtained values of expressivity parameters are associated to each gestures of B. These gestures are finally sent to the *behavior realizer* that outputs the animation parameters filtered and altered by the agent social attitude.

5 Conclusion and future works

In this paper we have proposed a computational model that enables an agent to convey social attitude through nonverbal behaviors. Based on studies in Human and Social Sciences, functions have been defined to inhibit or emphasize some behaviors and to generate specific gestures according to the agent dominance and friendliness. The computational model has been integrated within a SAIBA-like architecture by introducing three new modules. This model takes as input the communicative intentions, the possible signals associated, a table of influence based on the literature of Human and Social Sciences, the gender and the social attitude of the agent. For now we have considered that the social attitude was an available data but it should be explained in futire works how it is computed based on the goals and the social relations of the agent. The outputs are probabilities and expressivity parameters for the potentials signals. This model is a first step for generating nonverbal behaviors influenced by the social attitude an agent wants to convey. We are placing ourselves in the context of a virtual agent but this model could also be used for a robotic agent as the SAIBA architecture is also used in this domain [26].

The next step is the implementation and the validation of such a model through user perceptive studies. Moreover, our model presents some limits. For instance, the proposed table is built from the studies of psychologies we found so far and therefore does not consider every nonverbal behavior. For instance, there are some important cues generated with speech. Tone, volume, speed of voice can change, depending on the social attitude. Also, mimicry is an important factor to express social attitude that is not considered yet in the proposed model. Moreover, in the presented work, as a first step, we have modeled the results extracted from Human and Social Science with discrete values (-1,0 and 1) to represent the influence of social attitude on nonverbal behaviors. We aim at collecting real data on the user's nonverbal behavior while expressing a social attitude to improve the proposed model and retrieve more precise values.

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