Social Attitude Towards A Conversational Character

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Abstract—**This paper describes our experience with the design, implementation and validation of a user model for adapting health promotion dialogs with ECAs to the attitude of users toward the agent. The model was conceived in agreement with the theory of social emotions in communication. It integrates a linguistic parser with a dynamic Bayesian network and was learnt from a corpus of data collected with a Wizard of Oz study.**

I. Introduction

Affective states vary in their degree of stability, ranging from long-standing features (personality traits) to more transient ones (emotions). Other states, such as 'interpersonal stance' are in a middle of this scale: they are initially established by individual features like personality, social role, relationship between the interacting people and others but may be changed, in valence and intensity, by episodes occurring during interaction. After several forms of 'anthropomorphic behaviour' of users towards technologies were demonstrated [1], various terms and concepts have been employed to denote this behaviour and describe it. Some authors talk about *empathy* [2]; others attach to this term a meaning which goes beyond pure transmission of emotions: *"The empathor empathizes not only with the empathee's emotions but also with his physical state and other parameters of existence"* (S. Vaknin: On empathy.http://samvak.tripod.com/empathy.html). Hoorn and Konijn [3] talk about *engagement, involvement*, *sympathy* and their contrary, *distance*. Cassell and Bickmore [4] refer to Svennevig's theory of *interpersonal relations*. We adopt Scherer's concept of *interpersonal stance* as a category which is *"characteristic of an affective style that spontaneously develops or is strategically employed in the interaction with a person or a group of persons, coloring the interpersonal exchange in this situation (e.g. being polite, distant cold, warm, supportive, contemptuous)":* http://emotion-research.net/deliverables/D3e%20final.pdf.

In particular, we will talk of *interpersonal warmth* to denote "*the pleasant, contented, intimate feeling that occurs during positive interactions with friends, family, colleagues and romantic partners...[and]... can be conceptualized as... a type of relational experience, and a dimension that underlines many positive experiences."* [5]. In the ongoing research described in this paper, we wish to examine whether and how this form of communication may occur in short interaction sequences with an Embodied Conversational Character (ECA) and how it can be recognized so that the ECA may dynamically adapt its behaviour to it.

In the last few years, several projects aimed at recognizing the 'emotional state' of the user by considering a discrete set of 'basic emotions', some 'emotionally-related state' such as 'uncertainty' or some basic components of emotions, such as valence or intensity [6,7,8,9,10]. Other projects aimed at recognizing some personality trait of the users (extraversion) from the language style they employed in emails [11]. In these emotion recognition initiatives, the considered units of analysis are 'dialog turns' or some parts of them. Methods employed combine characterization of individual units in terms of a variety of acoustic and linguistic features with some classification method (discriminant analysis, naive Bayes, neural networks and others). The final goal is to classify a dialog turn of the user into one of a few (discrete or dimensional) emotional categories, independently of the context in which the move was uttered and of the dialogue history. Despite the good recognition accuracy obtained, consideration of the context seems now to be a key factor for improving this accuracy, so that some of the authors plan to include context among the variables they wish to consider in the move classification task [10]. If context may be seen as an additional variable in emotion recognition, its role in recognizing the social attitude of users towards technology is much more important. As we said, social attitude is not a short-term state like emotion, nor is it a long-term feature like personality. Users may establish with an artifact an initial attitude which depends on their personality, their background, their expectations from the artifact itself and other long-term or mid-term features. This initial attitude may then gradually change during interaction, according to the artifact's behaviour: how it responds to the user goals, how 'pleasant' and 'engaging' it is etc. This change cannot be assumed to be monotonic: both 'negative' and 'positive' events may occur during the dialog, which produce more or less important variations in the user attitude, in opposite directions: overall, the user attitude in a given phase of the dialog will be a function of the user's stable characteristics, of the dialog history, and of what the artifact just did.

In this paper, we describe two Wizard of Oz studies which were aimed at assessing how the social attitude of users towards an ECA is influenced by the interaction mode

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(text-based vs speech-based). We describe how the two corpora of dialogs collected with these studies were analyzed and how we built and validated a dynamic model of the social attitude of the user towards the ECA. Although the application domain is very specific (suggestions about healthy dieting), the general idea behind the methods employed may be extended to other domains.

II. Some Preliminary Questions

Some objections may be advanced to our attempts to apply, to user-ECA interactions, theories that were built on human-human relationships. Let us consider and argue on some of them.

Is it reasonable to presume that humans will show some sort of social attitude in these dialogs? Social relations may require time to be established: warm interactions are typical of friendship and long-term work teams and although immediate affective reactions may occur also in interactions with unknown people, these are usually occasional and of lower intensity. Therefore, in studying human-ECAs dialogs one may only expect to find subtle and irregular forms of affect display in users, and not in all users.

What provokes affect in communication? To several authors, expectancy violations or exceeding produce (respectively) negative or positive reactions. The user's goals and expectations in interacting with the ECA may therefore influence their social attitude during the dialog.

How may social attitude be displayed? Although non verbal manifestations of this relationships tend to prevail, several experimental studies proved that verbal expressions such as self-disclosure, emotional expressiveness, verbal immediacy and use of personal idioms occur as well [5].

Why should ECAs reciprocate these manifestations of (warm or cold) social attitude, and in which way? We claim that, if the ECA wants to strengthen its persuasion power towards the user, reciprocating warm social attitude may contribute to achieve this goal. The positive effects of this kind of adaptation was proved in other projects, in which users who experienced social conversations and small talk showed higher ratings in their sense of social connection to the agent [12].

III. Two Example Dialogs

We start with two example dialogs in the mentioned application domain which were extracted from our corpus and translated from Italian to English. In the first of them, the user just answers the agent's questions with a 'cold' attitude:

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Oz: Hi, my name is Valentina. I'm here to suggest you how to improve your diet. Which are your dietary habits?
Subject: Breakfast, lunch and dinner
Oz: What did you eat at lunch?
Subject: Pasta, fish, vegetables, fruits
Oz: What did you eat at breakfast?
Subject: Milk with coffee
Oz: Do you like fruits and vegetables?
Subject: Not much
Oz: Are you attracted by sweets?
Subject: Yes
...

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In the second example, the user gets more involved in the dialog and adopts a warmer interaction style:

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Oz: Hi, my name is Valentina. I'm here to suggest you how to improve your diet
Subject: Hi, my name is Carlo and I'm happy to chat with you.
Oz: Good. Then, tell me: which are your dietary habits?
Subject: Quite irregular, especially in summer, when I tend to eat frequently and untidily during the day.
Oz: But do you like eating, in general?
Subject: A lot: but I try to pay attention to what I eat, because I care for my shape and wouldn't like to become fatty.
Oz: Sage attitude! What did you eat at lunch, for instance?
Subject: Only some pasta, because I have a toothache
Oz: Really? I'm sorry, that's really unpleasant! But in general, when you are in good health, do you like fruits and vegetables?
Subject: I don't eat much fruits, but a lot of vegetables. Do you find it strange?

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In the two cases, after the first move the ECA adapts its dialog style to the user attitude, by changing content and style of its moves.

IV. A Wizard of Oz (WoZ) Tool

To collect data about the user attitude towards an ECA, we employed a WoZ tool [13] in which the application domain and the ECA's appearance may be settled at the beginning of simulation. In the studies described in this paper, the application domain was (as we said) healthy eating, while the ECA was a quite realistic agent with a young woman's appearance which was implemented with a commercial graphical software (http://www.haptek.com) and a text-to-speech synthesizer (http://www.loquendo.com): see figure 1.

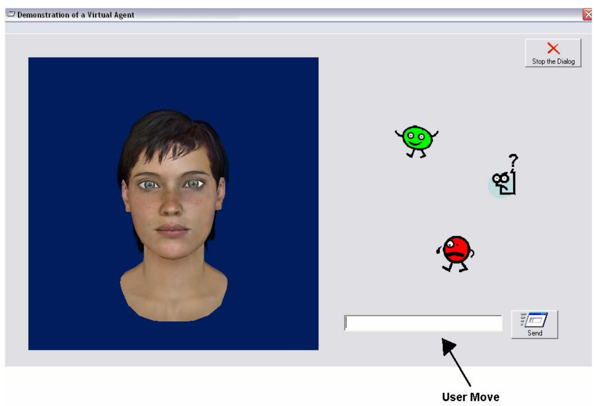

Fig. 1. The ECA employed in our studies.

A scenario was displayed to the subject at the interaction start to describe the application domain and the dialog goals. To insure that the wizard followed a consistent logic through all the study, the dialog plan to apply was specified in a document. To enable the users to provide their subjective evaluation of individual ECA's moves, three icons were displayed on the subject side (right side of figure 1): this type of evaluation was not compulsory. On the contrary, a questionnaire was displayed at the end of interaction, to ask subjects to evaluate the information provided during the dialog (how much credible, persuasive, etc it was) and the agent behaviour (how much competent, sincere etc it was). A log of the dialog was stored to analyse the subject's behaviour in more detail.

V. TWO STUDIES

In the two WoZ studies, only the interaction mode was varied. In the first of them, subjects interacted with the ECA via the keyboard; in the second one, they could interact with speech and via a touch screen. In both cases, subjects were invited to express themselves freely: they could just answer the agent questions or take the initiative in the dialog by making comments and asking questions. We defined two measures of the subject's *social attitude* during the dialog: a) *level of involvement*, as a function of the dialog duration and of the average length (in characters) of the subject moves, and b) *degree of initiative*, as a function of the percentage of questions raised by the subject over all the dialog moves. In addition, we defined a list of 'signs of social attitude' that we subjectively recognized in the language employed (in the first study) or in the speech (in the second one). We defined, accordingly, two markup languages to annotate the two corpora of and asked three independent raters to annotate them.

VI. STUDY 1: TEXT-BASED INTERACTION

The first study involved *30 subjects* between 23 and 30 years of age, equidistributed in gender and background (humanities or computer science). The dialogs included 712 move pairs overall. As shown in Table 1, there was a high variability in the two measures of level of involvement: the dialog duration ranged from 9 to 60 moves; the average length of moves ranged from 29 to 95 characters. The level of initiative of subjects was quite high, as about 30% of their moves were questions.

Subjects displayed their social attitude towards the agent through various 'signs' in the language employed (table 2): familiar style, questions about the agent's 'private life', humor, self-disclosure and friendly greetings and farewells [5,8]. The percentage of moves with these signs was associated positively with the level of involvement in the dialog, while it was correlated negatively with the level of initiative. As for the role of 'stable' user characteristics, the subjects' background was the factor which mostly influenced their behaviour: computer scientists made dialogs with less and shorter moves, a larger proportion of questions and a lower proportion of social moves than subjects with a background in humanities. We interpreted this difference in terms of difference of goals in the two categories of users. In the social expectations model, when expectations are negatively violated, negative relational change occurs; when they are exceeded, positive relational changes will occur; when they are confirmed, no relational change is predicted to occur. In our study, computer science subjects were students at different degrees (from undergraduate to PhD): they were experienced computer users, informed about trends of research in HCI and artificial intelligence. Their low social response might therefore be explained by their high level of expectation towards the application they were testing: rather than being engaged in the conversation, they seemed to challenge the application with tricky questions.

TABLE I
MEASURES OF SOCIAL ATTITUDE

	Text-based interaction	Speech-based interaction
Dialog duration	9-60 moves	14-55 moves
Move length	29-95 characters	17-276 characters
Av.% of questions	30.5	23.4
% of social moves	30.5	46.8

TABLE II
SIGNS OF SOCIAL ATTITUDE IN TEXT-BASED INTERACTION

Variable name, with definition	**Agr. rate**	**Kappa**
Friendly self-introduction [Yes/No] Whether the subject introduces himself with a friendly attitude (e.g. by giving his name or by explaining the reasons why he is participating in the dialog	.98	.87
Familiar style [Yes/No] Whether the subject employs a current language, dialectal forms, etc	.33	.16
Talks about self [Yes/No] Whether the subject provides information about self which was not explicitly requested by the agent	.73	.64
Personal questions about the agent [Yes/No] Whether the subject asks private information to the agent or tries to reciprocate suggestions	.70	.56
Humor [Yes/No] Whether the subject makes any kind of verbal joke in his move	.84	.36
Comments on the dialog [Positive/Negative] Whether the subject makes any kind of comment on the agent behaviour in the dialog	.82/.86	.42
Friendly farewell [Yes/No] Whether the subject requests to carry-on the dialog or employs any friendly form of leave	.93	.65

VII. STUDY 2: SPEECH-BASED INTERACTION

In the second study, we collected *14 dialogs* (and 434 move pairs overall) from subjects similar to those in the first one. The dialog duration was not significantly different from the first study but there was a neat difference in the move length and in the degree of initiative (see, again, Table 1). Apparently, personality played a strong role in this type of interaction: some subjects seemed to be quite intimidated, while others behaved much more naturally than with the keyboard interaction and tended to establish some sort of human-like relationship with the agent. The signs of social attitude we could notice from speech were not identical to those we noticed in text-based interaction. Like in that interaction mode, there were several examples of positive and negative comments and friendly style that we could notice from speech intonation. But we could notice, as well, several signs of reflection (doubt and uncertainty), politeness (encouragement and apologizing) and also smiling and also some laughters. Analysis of the acoustic properties of subjects' moves in this corpus is the subject of an ongoing cooperation with the University of Erlangen, in the scope of the HUMAINE European Project.

VIII. User Model As A Dynamic Bayesian Network

The user model was built on the first corpus of dialogs. As a first step, we implemented a keyword-based parsing algorithm for recognizing the signs of social attitude: the algorithm combined knowledge about the sign semantic with analysis of word salience [3]. Sensitivity ranged from .16 for 'negative comments' to .91 for 'friendly self introduction', while specificity was higher (from .79 for 'talks about self' to .98 for 'friendly self-introduction' and 'negative comments').

Results of parsing are integrated with variables describing context and stable characteristics (table 3) in a dynamic bayesian network [19], to recognize how the social attitude of the user evolves during the dialog. This considers the stable user characteristics: gender (Gend) and background (Back) to assign a prior probability distribution to the monitored variable: the social attitude of the user towards the ECA (Satt). After every user move, the model revises its image of the user after every move by considering the context in which the move was entered (previous ECA's move: Ctext), its type (Mtype) and its linguistic features. Uncertainty in the relationships among the various components is treated probabilistically. We employed DBNs as 'strictly repetitive models', in which the structure and parameters of individual time slices is identical and temporal links between couples of consecutive time slices are the same. Every time slice corresponds to a user move and temporal links are established only between values of the 'monitored' variable (Satt) at two consecutive time slices.

We employed results of annotation and parsing in the corpus of dialogs to learn structure and parameters of the model. Learning a dynamic bayesian network from data involves learning both atemporal and temporal parameters:

- in learning the atemporal part of our DBNs, we took every single user move in the corpus as an independent observation and applied the K2 algorithm [14]. Given a database D, this algorithm seeks the BN structure G that maximizes the probability P(G|D) by applying a greedy heuristic. A search order is set for the nodes in the network: this implies setting a direction of the arcs and a hierarchy in the relative position of nodes in the network. In our case, results of parsing came first in the list, followed by signs of social attitude, the monitored variable, context and finally stable characteristics. This algorithm is appropriate, we believe, in learning user models in which links among nodes have a specified meaning and orientation, 'trigger variables' correspond to root nodes and 'observable' ones to leaf nodes. However, K2 tries to find the model that fits data best by maximizing a given measure of validity (the logarithm of the likelihood) but does not care about the use of the resulting model: therefore, the learnt model is not necessarily the best when used for making predictions. We therefore applied the learning algorithm interactively, by checking the plausibility of learned links and the problems due to 'sparse data' and by introducing, if needed, new links to avoid problems due to d-separation.
- In learning the temporal link between the monitored variable Satt at two subsequent time instants, we took every dialog as an observation to measure the conditional probability that Satt takes a given value at time t, given its value at time t-1.

TABLE III
VARIABLES IN THE MODEL

Variable category	Variable name	Label
Stable user characteristics	Background	Back
	Gender	Gend
Context	Type of last agent move	Ctext
	Type of user move	Mtype
Monitored variable	User attitude towards the agent	Satt
Signs of social attitude	Familiar style	Fstyl
	Friendly self-introduction	Fsint
	Talks about self	Perin
	Questions about agent	Qagt
	Friendly farewell	F-Fw
	Comments	Comm
Results of parsing	Cues of familiar style	Pfstyl
	Cues of friendly self introduction	Pfsint
	Cues of talks about self	Pperin
	Cues of questions to the agent	Pqagt
	Cues of friendly farewell	Pffw
	Cues of comments	Pcomm

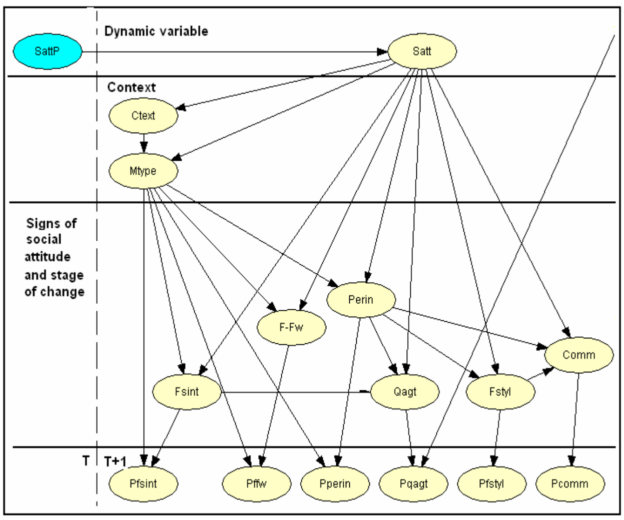

Fig. 2. A generic time slice in the dynamic user model

The model learnt is shown in figure 2: node labels should be interpreted as described in table 3. The model slide at time 0 (not displayed in the figure) shows that a background in humanities implies a higher likelihood of ‘warm’ social attitude toward the agent and of friendly self introduction in particular. The following, generic time slice (in figure 2) shows that, for instance, friendly self-introduction and comments are influenced by social attitude: when the level of social attitude is low, self introduction is usually omitted by the user to make questions to the agent, and few comments are made after agent's answers or suggestions. The use of familiar style is associated with talking about self, especially in comments or answers to agent's questions; questions about the agent often come after friendly self-introduction, ... and so on.

Table 4 shows an example of application of the model to one of the dialogs in the training corpus: W stands for ‘wizard’ and S for ‘subject’. As the subject’s background is in humanities, the initial probability that she will establish a social relationship with the ECA is .61. This value grows to .71 after the first move. No sign of social attitude is displayed at moves 2, 9, 10 and the probability of a warm Satt goes down. Other moves show signs of talks about self, familiar style or friendly farewell and the probability of a warm Satt increases.

Model validation was performed in two steps: a) in internal validation, its results were compared with the majority voting of raters (the evaluation expressed by two over the three of them); b) in external validation, it was applied to a new test set of 5 dialogs. We examined how a variation in the threshold of the probability of the monitored variable (Satt) affects sensitivity and specificity of the model in recognizing this feature.

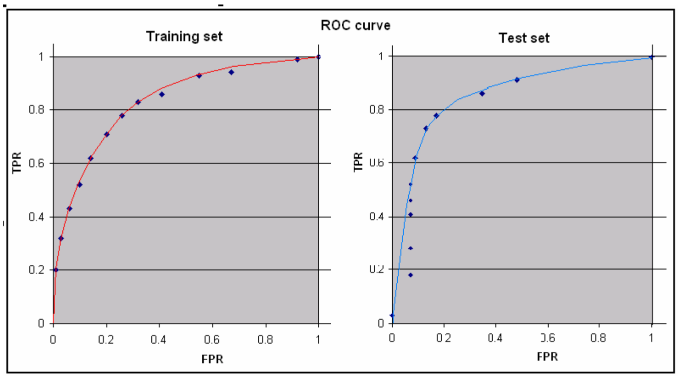

Fig. 3. ROC curves for the training set and the test set.

The Receiver Operating Characteristics (ROC) curve in the left side of figure 3 shows this trend. The curve illustrates the tradeoff between true positive rate (TPR) and false positive rate (FPR); it may be employed to measure the accuracy of the model and to select the cut-off point which insures the best percentage of correctly classified cases (%CCC) or the optimum equilibrium between sensitivity

TABLE IV

SIMULATION OF THE USER MODELING ALGORITHM

N	Adjoint pairs	P(Satt)
1	W: Hi, my name is Valentina. I’m here to suggest you how to improve your diet. Do you want to talk me about your eating habits? S: I usually have yogurt and a little sweet at breakfast; various things at lunch and dinner. *(Pperin)*	0.71
2	W: Do you like eating? S: Reasonably	0.50
3	W: What do you think of a good dish of spaghetti? S: A good dish of spaghetti is tempting and would be OK now! *(Pfstyl)*	0.78
4	W: Are you attracted by sweets? S: Enough. I like both preparing and eating them... *(Pperin)*	0.75
5	W: Do you think that your diet is correct or would you like to change it? S: I think I would need a more regular regimen. *(Pperin)*	0.74
6	W: Did you ever think to change your diet? S: Yes, sometimes I did it and got very good results. Now, either because of my laziness or m stressing rythms I can’t lay myself into more regular habits. *(Pperin)*	0.74
7	W: Do you believe your weight is correct or would you like to change it in any way? S: Unfortunately it is not ideal. I would like to change it and come back to my weight of a few years ago. *(Pperin)*	0.74
8	W: Try to remember everything you eat daily: do you believe you take all the substances you would need? S: I think I take all the substances I need... and maybe even some more. *(Pperin)*	0.74
9	W: Tell me: is there any aspect of diet on which you would like be informed? I may try to answer, although my knowledge is still incomplete. S: Is there a diet which enables one to eat anything without risking to get fat?	0.51
10	W: There are not ‘good’ or ‘bad’ foods, but only good or bad diets. Any food may be part of a healthy life style...ect S: Also fried and hypercaloric foods?	0.44
11	W: Many people like fried food which, however, should be limited as much as possible...etc S: OK, thanks for the information. *(Pffw & Pfstyl)*	0.96

and specificity. In our training set, the best %CCC (.75) is reached in a range of cut-off points in which the sensitivity goes from .78 to .83 and the specificity from .74 to .68. The ROC curve for the test set is shown in the right side of the same figure: the predictive values of the model for the training and the test set are similar (.79 vs .75).

Analysis of incorrectly classified cases in the two sets shows that these are mainly due to moves in which the parser was not able to recognize the signs of social attitude displayed by the subject: typically, familiar style and positive or negative comments (for which the parser’s sensitivity was low) and irony, which we did not attempt to recognize. In those cases, knowledge of the context repaired in part the parser’s failure. We are employing this user model in the simulation of persuasion dialogs. Here, individual signs of social attitude displayed in a move produce immediate reactions of the ECA, while the dynamic, overall image of social attitude is employed to drive the dialog planning process. Our next step will be to include results of speech analysis in the belief network to increase its recognition accuracy. This is a promising perspective, considering that, as we said when describing results of the two studies, linguistic and acoustic features seem to be complementary in recognizing signs of social attitude.

IX. Final Considerations

While considerable efforts are being made to recognize individual emotions or their valence and arousal, as far as we know there is much less experience in trying to recognize social attitude towards technology. What is new in the research described in this paper is our attempt to recognize whether and how the user manifests some kind of interpersonal warmth towards the ECA and to monitor how this attitude evolves during the dialog. We were inspired by previous work on recognition of attitudes, personality and emotions from language. Litman and Forbes and Lee et al [9,10] worked on tutorial dialogs to identify emotional states by combining acoustic and linguistic information. Ang et al [6] worked on annoyance and frustration in telephone-based dialogs, Gill and Oberlander [13] recognized extraversion /intraversion in email texts from language features. In analyzing call center dialogs and human-robot communication, Batliner et al focused on signs of interpersonal relations rather than full blown emotions [6].

In attempting to recognize interpersonal warmth by combining a simple parser with representation of context and user background, we got a similar recognition rate to that achieved in the cited studies. The quite good results we have got in modelling a fuzzy concept like ‘social attitude’ was due to translating into our DBNs the theories behind this concept, that is the signs through which this attitude is manifested. Application of WoZ studies to the design of ECAs has some antecedents in affective computing [15], as well as application of belief networks to user modeling [16, 17, 18].

The main limit of our studies is that they did not involve people who spontaneously asked to receive information about healthy eating: our assumption was that the kind of relationship our subjects established with the ECA was similar to the relationship a subject in need of help would establish with it. The characteristics of our subjects were similar (in age and background) to those of potential users and therefore we claim that this was a good experimental setting to train the user model. The collected corpus was not very large, and this produced some problems of ‘sparse data’ that are common in this kind of studies. In spite of these limits, the validity of the model was quite good and will likely be improved after refining the parser and including results of speech analysis. Another limit of our method is in the length of user-ECA interactions: an effective support should rely on repeated encounters with subjects which would probably produce a closer user-ECA relationship.

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