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# Adaptation Mechanisms in Human-Agent Interaction: Effects on User's Impressions and Engagement

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## 2 ABSTRACT

3 Adaptation is a key mechanism in human-human interaction. In our work, we aim at endowing  
4 embodied conversational agents with the ability to adapt their behaviour when interacting with a  
5 human interlocutor. With the goal to better understand what are the main challenges concerning  
6 adaptive agents, we investigated the effects on user's experience of three adaptation models for  
7 a virtual agent. The adaptation mechanisms performed by the agent take into account user's  
8 reaction and learn how to adapt on the fly during the interaction. Agent's adaptation is realised  
9 at several levels (i.e., at behavioural, conversational and signal level) and focuses on improving  
10 user's experience along different dimensions (i.e., user's impressions and engagement). In our  
11 first two studies, we aim to learn agent's multi-modal behaviours and conversational strategies to  
12 optimise dynamically user's engagement and impressions of the agent, by taking them as input  
13 during the learning process. In our third study, our model takes as input both the user's and the  
14 agent's past behaviour and predicts the agent's next behaviour. Our adaptation models have been  
15 evaluated through experimental studies sharing the same interacting scenario, with the agent  
16 playing the role of a virtual museum guide. These studies showed an impact of the adaptation  
17 mechanisms on user's experience of the interaction and their perception of the agent. Interacting  
18 with an adaptive agent vs a non-adaptive agent tended to be more positively perceived. Finally,  
19 the effects of people's a-priori about virtual agents found in our studies highlight the importance  
20 to take into account user's expectancies in human-agent interaction.

21 **Keywords:** Human-agent interaction, Adaptation Mechanisms, Engagement, Impressions, Embodied Conversational Agents

## 1 INTRODUCTION

22 During an interaction, we communicate through multiple behaviours. Not only speech, but also our facial  
23 expressions, gestures, gaze direction, body orientation, etc. participate to the message being communicated  
24 (Argyle, 1972). Both interactants are active participants in an interaction and adapt their behaviours to  
25 each other. This adaptation arises on several levels: we align ourselves linguistically (vocabulary, syntax,  
26 level of formality), but we also adapt our non-verbal behaviours (e.g., we respond to the smile of our  
27 interlocutor, we imitate their posture, their gestural expressiveness), our conversational strategies (e.g.,  
28 to be perceived warmer or more competent), etc (Burgoon et al., 2007). This multi-level adaptation can  
29 have several functions, such as reinforcing engagement in the interaction, emphasising our relationship

30 with others, showing empathy, managing the impressions we give to others (Lakin and Chartrand, 2003;  
31 Fischer-Lokou et al., 2011; Gueguen et al., 2009). The choice of verbal and non-verbal behaviours and  
32 their temporal realisation are markers of adaptation.

33 Embodied Conversational Agents, ECAs, are virtual entities with a human-like appearance that are  
34 endowed with communicative and emotional capabilities (Cassell et al., 2000). They can display a wide  
35 range of multi-modal expressions to be active participants in the interaction with their human interlocutors.  
36 They have been deployed in various human-machine interactions where they can act as tutor (Mills et al.,  
37 2019), health support (Zhang et al., 2017; Lisetti et al., 2013; Rizzo et al., 2016), companion (Sidner  
38 et al., 2018), museum guide (Swartout et al., 2010; Kopp et al., 2005), etc. Studies reported that ECAs  
39 are able to take into account their human interlocutors and show empathy (Paiva et al., 2017), display  
40 backchannels (Bevacqua et al., 2008), build rapport (Huang et al., 2011; Zhao et al., 2016). Since its  
41 relevance in human-human interaction, adaptation could be exploited to improve natural interactions with  
42 ECAs. It seems thus important to investigate whether an agent adapting to user's behaviours could provoke  
43 similar positive outcomes in the interaction.

44 The majority of works in this context developed models learnt from existing databases of human-human  
45 interaction and did not consider the dynamics of adaptation mechanisms during an interaction. We are  
46 interested in developing an ECA that exploits how the interaction is currently going and is able to learn in  
47 real-time what is the best adaption mechanism for the interaction.

48 In this paper we report 3 studies where an ECA adapts its behaviours by taking into account user's  
49 reaction and by learning how to adapt on the fly during the interaction.

50 The goal of the different studies is to answer two broad research questions:

51 *“Does adapting an ECA's behaviours enhance user's experience during interaction?”*;

52 *“How does an ECA which adapts its behaviour in real-time influence the user's perception of the agent?”*

53 User's experience can involve many factors and can be measured by different dimensions, such as user's  
54 engagement and user's impressions about the ECA (Burgoon et al., 2007). In our 3 studies that we report in  
55 this paper, we implemented three independent models where agent's adaptation is realised at several levels  
56 and focuses on improving user's experience along different dimensions:

- 57 1. Agent's adaptation at a behavioural level: the ECA adapts its behaviours (e.g., gestures, arms rest  
58 poses, smile) in order to maximise user's impressions about agent's warmth or competence, the two  
59 fundamental dimensions of social cognition (Fiske et al., 2007). This model is described in Section 7;
- 60 2. Agent's adaptation at a conversational level: the ECA adapts its communicative strategies to elicit  
61 different levels of warmth and competence, in order to maximise user's engagement. This model is  
62 described in Section 8;
- 63 3. Agent's adaptation at a signal level: the ECA adapts its head and eyes rotation and lip corners movement  
64 in function of user's signals in order to maximise user's engagement. This model is described in Section  
65 9.

66 Each adaptation mechanism has been implemented in the same architecture that allows an ECA to adapt  
67 to the non-verbal behaviours of the user during the interaction. This architecture includes a multi-modal  
68 analysis of user's behaviour using the Eyesweb platform (Camurri et al., 2004), a dialogue manager (Flipper  
69 (van Waterschoot et al., 2018)) and the ECA GRETA (Pecune et al., 2014). The architecture has been  
70 adapted to each model, and evaluated through experimental studies. The ECA played the role of a virtual

71 guide at the Science Museum of Paris. The scenario used in all the evaluation studies is described in Section  
72 6.

73 Even though these 3 models have been implemented in the same architecture and tested on the same  
74 scenario, they have not been developed in order to do comparative studies. The main goal of this paper  
75 is to frame them in the same theoretical framework (see Section 2) and have insights about each of these  
76 different adaptation mechanisms, to better understand what are the main challenges concerning these  
77 models and to suggest further improvements for an adaptation system working on multiple levels.

78 This paper is organised as follows: in Section 2 we review the main theories about adaptation which our  
79 work relies on, in particular Burgoon and colleagues' work; in Section 3 we present an overview of existing  
80 models that focus on adapting the ECA's behaviour according to user's behaviour; in Section 4 we specify  
81 the dimensions we focused on in our adaptation models; in Section 5 we present the general architecture we  
82 conceived to endow our ECA with the capability of adapting its behaviour to user's reactions in real-time;  
83 in Section 6 we describe the scenario we conceived to test the different adaptation models; in Sections  
84 7, 8 and 9 we report the implementation and evaluation of each of the three models. More details about  
85 them can be found in our previous papers (Biancardi et al., 2019b,a; Dermouche and Pelachaud, 2019). We  
86 finally discuss the results of our work and possible improvements in Sections 10 and 11 respectively.

## 2 BACKGROUND

87 Adaptation is an essential feature of interpersonal relationship (Cappella, 1991). During an effective  
88 communication, people adapt their interaction patterns to one another (e.g., dancers synchronise their  
89 movements, people adapt their conversational style in a conversation). These patterns contribute to define  
90 and maintain our interpersonal relationships, by facilitating smooth communication, fostering attraction,  
91 reinforcing identification with an in-group, increasing rapport between communicators (Giles et al., 1991;  
92 Bernieri et al., 1988; Chartrand and Bargh, 1999; Gallois et al., 2005).

93 There exist several adaptation patterns, differing according to their behaviour type (e.g., the modality,  
94 the similarity to the other interlocutor's behaviour, etc), their level of consciousness, whether they are  
95 well decoded by the other interlocutor, and according to their effect on the interaction (Toma, 2014).  
96 Cappella and colleagues (Cappella, 1981) consider an additional characteristic, that is, adaptation can be  
97 asymmetrical (unilateral), when only one partner adapts to the other, or symmetrical (mutual), like in the  
98 case of interaction synchrony.

99 In line with these criteria, in some examples of adaptation people's behaviours become more similar  
100 to one another. This type of adaptation is often unconscious and reflects reciprocity, or convergence.  
101 According to Gouldner (Gouldner, 1960), reciprocity is motivated by the need to maintain harmonious  
102 and stable relations. It is contingent (i.e., one person's behaviours are dependent upon the other's) and  
103 transactional (i.e., it is part of an exchange process between two people).

104 In other cases, adaptation can include complementarity, or divergence: this occurs when the behaviour of  
105 one person differs from but complements that of the other person.

106 Several theories focus on one or more specific characteristics of adaptation and highlight different factors  
107 that drive people's behaviours. They can be divided into 4 main classes, according to the perspective they  
108 follow to explain adaptation.

109 The first class of theories includes biologically based models (e.g., (Condon and Ogston, 1971), (Bernieri  
110 et al., 1988)). These theories state that individuals exhibit similar patterns to one another. These adaptation  
111 patterns have an innate basis, as they are related to satisfaction of basic needs like bonding, safety, social

112 organisation. Their innate bases make them universal and involuntary but they can be influenced as well by  
113 environmental and social factors.

114 Following a different perspective, arousal-based and affect-based models (e.g., (Argyle and Dean, 1965),  
115 (Altman et al., 1981), (Cappella and Greene, 1982)) support the role of internal emotional and arousal  
116 states as driving factors of people's behaviours. These states determine approaching or avoiding behaviours.  
117 This group of theories explains the balance between compensation and reciprocity.

118 Social-norm models (e.g., (Gouldner, 1960), (Dindia, 1988)) do not consider the role of physiological or  
119 psychological factors but argue for the importance of social phenomena as guiding forces. These social  
120 phenomena are for example the in-group or out-group status of the interactants, their motivation to identify  
121 with one another, their level of affiliation or social distance.

122 The last class of theories includes communication- and cognitive-based models (e.g., (Andersen, 1985),  
123 (Hale and Burgoon, 1984)), which focus on the communicative purposes of the interactants and on the  
124 meaning the behavioural patterns convey. While adaption happens mainly unconsciously, it may happen  
125 that the process of interpersonal adaptation may be strategic and conscious (Gallois et al., 2005; Giles et al.,  
126 1991).

127 The majority of these theories have been studied by Burgoon and colleagues (Burgoon et al., 2007). In  
128 particular, they examined fifteen previous models and considered the most important conclusions from  
129 the previous empirical research. From this analysis they came out with a broader theory, the Interaction  
130 Adaptation Theory (IAT). This theory states that we alter our behaviour in response to the behaviour  
131 of another person in conversations (Infante et al., 2010). IAT takes into account the complexities of  
132 interpersonal interactions by considering people's needs, expectations, desires and goals as precursors of  
133 their degree and form of adaptation. IAT is a communication theory made of multiple theories, and which  
134 focuses on sender's and receiver's process and patterns.

135 Three main interrelated factors contribute to IAT. Requirements (R) refer to the individual beliefs about  
136 what is necessary in order to have a successful interaction. R are mainly driven by biological factors, such  
137 as survival, safety, affiliation. Expectations (E) refer to what people expect from the others based on social  
138 norms or knowledge coming from previous interactions. E are mainly influenced by social factors. Finally,  
139 Desires (D) refer to individual's goals and preferences about what to get out of the interaction. D are mainly  
140 influenced by person-specific factors, such as temperament or cultural norms. These three factors are used  
141 to predict an individual's Interactional Position (IP). This variable derives from the combination of R, E  
142 and D, and represents the individual's behavioural predisposition that will influence how an interaction  
143 will work. The IP would not necessarily correspond to the partner's Actual behaviour performed in the  
144 interaction (A). The relation between IP and A will determine the type of adaptation during the interaction.  
145 For example, when IP and A almost match, IAT predicts behavioural patterns such as reciprocity and  
146 convergence. When A is more negatively valenced than IP, the model predicts compensation and avoiding  
147 behaviours.

148 In the work presented in this paper we rely on Burgoon's IAT theory. Indeed, our adapting ECA has an  
149 Interactional Position (IP), resulting from its Desires (D) and Expectations (E). In particular, the agent's  
150 Desire D is to maximise user's experience, and its Expectations E are about user's reactions to its behaviours.  
151 In our different models of adaptation mechanisms, agent's Desire D refers either to give the best impression  
152 to the user or to maximise user's engagement (see Section 4). Consequently, the Expectations E refer to  
153 user's reaction reflecting their impressions or engagement level in response to the agent's behaviour. The

154 behaviour that will be performed by the ECA depends on the relation between THE agent's IP and THE  
155 user's reaction (Actual behaviour A).

156 In addition, we explore different ways the ECA can adapt to user's reactions. On one hand, we focus  
157 on theories that consider adaptive behaviours more broadly than a mere matching, that is, adaptation as  
158 responding in appropriate ways to a partner. The ECA will choose its behaviours according to the effect  
159 they have on user's experience (see Section 7). In Study 2 (see Section 8), our adaptive agent follows the  
160 same perspective but by adapting its communicative strategies. On the other hand, we try to simulate a  
161 more unconscious and automatic process working at a motoric level: the agent adapts at a signal level (see  
162 Study 3, Section 9).

### 3 STATE OF THE ART

163 In this section, we present an overview of existing models that focused on adapting ECAs' behaviour  
164 according to user's behaviour in order to enhance the interaction and user's experience along different  
165 dimensions such as engagement, rapport, interest, liking etc. These existing models predicted and generated  
166 different forms of adaptation, such as backchannels, mimicry, voice adaptation, and were applied on virtual  
167 agents or robots.

168 Several works were interested in understanding the impact of adaptation on user's engagement and rapport  
169 building. Some of them did so through the production of backchannels. Huang et al. (2010) developed an  
170 ECA able to produce backchannels to reinforce the building of rapport with its human interlocutor. The  
171 authors used Conditional Random Fields (CRF) (Lafferty et al., 2001) to automatically learn when listeners  
172 produce visual backchannels. The prediction was based on three features: prosody (e.g., pause, pitch),  
173 lexical (spoken words) and gaze. Using this model, the ECA was perceived more natural; it also created  
174 more rapport with its interlocutor during the interaction. Schröder et al. (2015) developed a sensitive  
175 artificial listener able to produce backchannels. They developed a model that predicted when an ECA  
176 should display a backchannel and with which intention. The backchannel could either be a smile, nod, and  
177 vocalisation or an imitation of human's smile and head movement. Participants who interacted with an  
178 ECA displaying backchannels were more engaged compared to when no backchannels were shown.

179 Other works focused on modelling ECAs able to mimic their interlocutors' behaviours. Bailenson and  
180 Yee (2005) studied the social influence of mimicry during human-agent interaction (they referred at this  
181 as the chameleon effect). The ECA mimicked the user's head movements with a delay up to 4 seconds.  
182 An ECA showing mimicry was perceived as more persuasive and more positive than an ECA showing  
183 no mimicry at all. Raffard et al. (2018) also studied the influence of ECAs mimicking their interlocutors'  
184 head and body posture with some delay (below 4 seconds). Participants with schizophrenia and healthy  
185 participants interacted with an ECA that mimicked them or not. Both groups showed higher behaviour  
186 synchronisation and reported an increase of rapport in the mimicry condition. Another study involving  
187 mimicry was proposed in (Verberne et al., 2013) in order to evaluate if an ECA mimicking user's head  
188 movements would be liked and trusted more than a non-mimicking one. This research question was  
189 investigated by running two experiments in which participants played a game involving drivers handling  
190 over the car control to the ECA. While results differed depending on the game, the authors found that  
191 liking and trust were higher for a mimicking ECA than for a non-mimicking one.

192 Reinforcement learning methods for optimising agent's behaviours according to user's preference have  
193 been used in different works. For example, Liu et al. (2008) endowed a robot with the capacity to detect in  
194 real time the affective states (liking, anxiety and engagement) of children with autism spectrum disorder  
195 and to adapt its behaviour to children's preferences of activities. The detection of children's affective states

196 was done by exploiting their physiological signals. A large database of physiological signals was explored  
197 to find their interrelation with the affective states of the children. Then, an SVM-based recogniser was  
198 trained to match children's affective state to a set of physiological features. Finally, the robot learned the  
199 activities that children preferred to do at a moment based on the predicted liking level of the children  
200 using QV-learning (Wiering, 2005). The proposed model led to an increase in the reported liking level  
201 of the children towards the robot. Ritschel et al. (2017) studied the influence of agent's personality on  
202 user's engagement. They proposed a reinforcement learning model based on social signals for adapting  
203 the personality of a social robot to user's engagement level. User's engagement was estimated from their  
204 multi-modal social signals such as gaze direction and posture. The robot adapted its linguistic style by  
205 generating utterances with different degrees of extroversion using a Natural Language Generation approach.  
206 The robot that adapted its personality through its linguistic style increased user's engagement but the degree  
207 of user's preference toward the robot depended on the on-going task. Later on the authors applied similar  
208 approach to build a robot that adapts to the sense of humour of its human interlocutor (Weber et al., 2018).

209 Several works have been conducted in the domain of education where an agent, being physical as a robot  
210 or virtual as an ECA, adapted to the learner's behaviour. These works reported that adaptation is generally  
211 linked with an increase of the learner's engagement and performance. For example, Gordon et al. (2016)  
212 developed a robot acting as a tutor for children learning a second language. To favour learning, the robot  
213 adapted its behaviours to optimise the level of the children's engagement which was computed from their  
214 facial expressions. A reinforcement learning algorithm was applied to compute the robot's verbal and  
215 non-verbal behaviour. Children showed higher engagement and learned more second-language words with  
216 the robot that adapted its behaviours to children's facial expression, compared to the non-adaptive robot.  
217 Woolf et al. (2009) manually designed rules to adapt the facial expressions of a virtual tutor according to  
218 the student's affective state (e.g., frustrated, bored or confused). For example, if the student was delighted,  
219 respectively sad, the tutor might look pleased, respectively sad. Results showed that when the virtual tutor  
220 adapted its facial expressions in response to the student's ones, the latter maintained higher levels of interest  
221 and reduced boredom when interacting with the tutor.

222 Other works looked at adapting the activities undertaken by an agent during an interaction to enhance  
223 knowledge acquisition and reinforce engagement. In (Ahmad et al., 2017), a robot playing games with  
224 children was able to perform three different types of adaptations, game-based, emotion-based, and memory-  
225 based, that relied respectively on: i) the game state, ii) emotion detection from child's facial expressions, and  
226 iii) face recognition mechanisms and remembering child's performance. In the first category of adaptation,  
227 a decision making mechanism was used to generate a supporting verbal and non-verbal behaviour. For  
228 example, if the child performed well, the robot said "Wow, you are playing extra-ordinary" and showed  
229 positive gestures such as thumbs up. The emotion-based adaptation mapped the child's emotions to a  
230 set of supportive dialogues. For example, when detecting the emotion of joy the robot said: "You are  
231 looking happy, I think you are enjoying the game". For memory adaptation the robot adapted its behaviour  
232 after recognising the child and retrieving the child's game history such as their game performance and  
233 results. Results highlighted that emotion-based adaptation resulted in the highest level of social engagement  
234 compared to memory-based adaptation. Game adaptation did not result in maintaining long-term social  
235 engagement. Coninx et al. (2016) proposed an adaptive robot able to change activities during an interaction  
236 with children suffering of diabetes. The aim of the robot was to reinforce children's knowledge for  
237 managing their disease and well-being. Three activities were designed to approach the diabetes-learning  
238 problem from different perspectives. Depending on the children's motivation the robot switched between  
239 the three proposed activities. Adapting activities in the course of the interaction led to a high level of

240 children's engagement toward the robot. Moreover, this approach seemed promising for setting up long-term  
241 child-robot relationship.

242 In a task-oriented interaction, Hemminahaus and Kopp (2017) presented a model to adapt the social  
243 behaviour of an assistive robot. The robot could predict when and how to guide the attention of the user  
244 depending on the interaction contexts. The authors developed a model that mapped interactional functions  
245 such as motivating the user, guiding them, onto low-level behaviours executable by the robot. The high-level  
246 functions were selected based on the interaction context as well as the attentive and emotional states of  
247 the user. Reinforcement learning was used to predict the mapping of these functions onto lower-level  
248 behaviours. The model was evaluated in a scenario in which a robot assisted the user in solving a memory  
249 game by guiding their attention to the target objects. Results showed that users were able to solve the game  
250 faster with the adaptive robot.

251 Other works focused on voice-adaptation during social interaction. Voice-adaptation is based on acoustic-  
252 prosodic entrainment that occurs when two interactants adapt their manner of speaking, such as their  
253 speaking rate, tone, or pitch, to each other. Levitan (2013) found that voice-adaptation improved spoken  
254 dialogue systems performance and user's satisfaction. Lubold et al. (2016) studied the effect of voice-  
255 adaptation on social variables such as rapport and social presence. They found that social presence was  
256 significantly higher with a social voice-adaptive speech interface than with purely social dialogue.

257 In most of previous works, the adaptation mechanisms that have been implemented measured their  
258 influence on user's engagement through questionnaires. They did not include them as a factor of the  
259 adaptation mechanisms. In our first two studies reported in this paper, we aimed to learn agent's multi-  
260 modal behaviours and conversational strategies to optimise dynamically user's engagement and their  
261 impressions of the ECA, by taking them as input during the learning process.

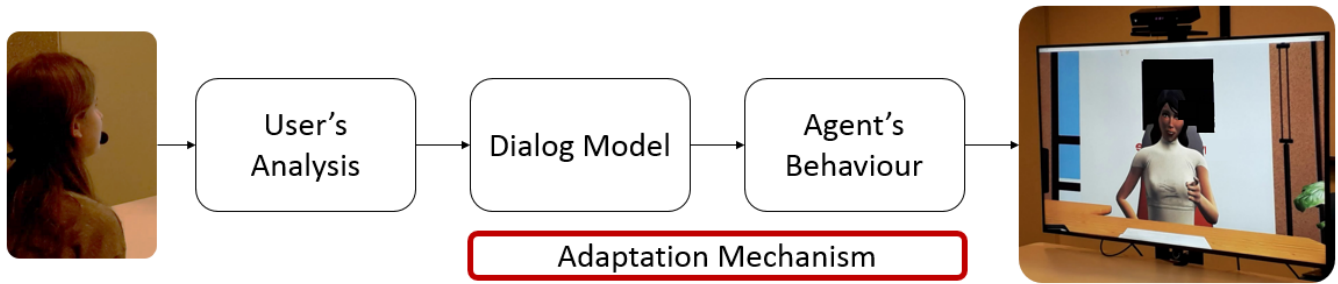
262 Moreover, in most existing works the agent's predicted behaviour depended exclusively on the user's  
263 behaviour and ignored the interaction loop between the ECA and the user. In our third study, we took into  
264 account this interaction loop, i.e., our model takes as input both, the user's and the agent's past behaviour  
265 and predicts the agent's next behaviour. Another novelty presented in our work is to include the agent's  
266 communicative intentions along with its adaptive behaviours.

#### 4 DIMENSIONS OF STUDY

267 In our studies we focused on adaptation in human-agent interaction, by using user's reactions as the input  
268 for agent's adaptation. In particular, we took into account two main dimensions, that are user's impressions  
269 of the ECA and user's engagement during the interaction.

270 These two dimensions play an important role during human-agent interactions, as they influence the  
271 acceptability of the ECA by the user and the willingness of interacting again with it (Bergmann et al.,  
272 2012; Bickmore et al., 2013; Cafaro et al., 2016). In order to engage the user, it is important that the ECA  
273 displays appropriate socio-emotional behaviours (Pelachaud, 2009). In our case, we were interested in  
274 whether and how the ECA could affect user's engagement by managing the impressions it gave to them. In  
275 particular, we considered user's impressions of the two main dimensions of social cognition, i.e., warmth  
276 and competence (Fiske et al., 2007). Warmth includes traits like friendliness, trustworthiness, sociability,  
277 while competence includes traits like intelligence, agency and efficacy. In human-human interaction,  
278 several studies showed the role of non-verbal behaviours in conveying different impressions of [warmth and](#)  
279 [competence](#). In particular, communicative gestures, arms rest poses and smiling behaviour have been found  
280 to be associated with different degrees of warmth and/or competence (Duchenne, 1990; Cuddy et al., 2008;





**Figure 1.** System architecture: in the *User's Analysis* module user's non-verbal and verbal signals are extracted and interpreted; user's reaction is sent to the *Dialog Model* module which computes the dialog act to be communicated by the ECA. The *Agent's Behaviour* module instantiates the dialog act into multi-modal behaviours to be displayed by the ECA. The *Adaptation Mechanism* module adapts the agent's behaviour to user's behaviour. Its placement in the architecture depends on the specific adaptation mechanism that is implemented.

281 Maricchiolo et al., 2009; Biancardi et al., 2017a). In the context of human-agent interaction, we can control  
 282 and adapt the non-verbal behaviours of the ECA during the flow of the interaction.

283 Following Burgoon's IAT theoretical model, our adapting ECA has thus the Desire D to maintain user's  
 284 engagement (or impressions) during the interaction. Since the ECA aims to be perceived as a social  
 285 entity by its human interlocutor, the agent's Expectancy E is that adaptation can enhance the interaction  
 286 experience. In our work we are interested in whether adapting at a behavioural or conversational level  
 287 (i.e., the agent's **warmth and competence** impressions) and/or at low-level (i.e., the agent's head and eyes  
 288 rotation and lip corners movement) could affect user's engagement. Even though the impact of agent's  
 289 adaptation on user's engagement has already been the object of much research (see Section 3), here we use  
 290 user's engagement as a real-time variable given as input for the agent's adaptation.

## 5 ARCHITECTURE

291 In this Section we present the architecture we conceived to endow the ECA with the capability of adapting  
 292 its behaviour to user's reactions in real-time. The architecture consists of several modules (see Figure  
 293 1). One module extracts information about user's behaviours using a Kinect and a microphone. This  
 294 information is interpreted in terms of speech (what the user has uttered) and user's state (e.g., their  
 295 engagement in the interaction). This interpreted information is sent to a dialog manager that computes the  
 296 communicative intentions of the ECA, that is, what it should say and how. Finally, the animation of the  
 297 ECA is computed on the fly and played in real-time. The agent's adaptation mechanisms are also taken into  
 298 account when computing its verbal and non-verbal behaviours. The architecture is general enough to allow  
 299 for customisation of its different modules according to the different adaptation mechanisms and goals of  
 300 the agent.

301 In more details, the 4 main parts of the architecture are:

- 302 1. *User's Analysis*. The EyesWeb platform (Camurri et al., 2004) allows the extraction in real-time of:  
 303 (1) user's non-verbal signals (e.g., head and trunk rotation) starting from the Kinect depth camera  
 304 skeleton data; (2) user's facial muscular activity (Action Units AUs (Ekman et al., 2002)), by running  
 305 the OpenFace framework (Baltrušaitis et al., 2016); (3) user's gaze; (4) user's speech, by executing the  
 306 Microsoft Speech Platform<sup>1</sup>.

<sup>1</sup> <https://www.microsoft.com/en-us/download/details.aspx?id=27225>

307 These low-level signals are processed by EyesWeb and other external tools, such as machine learning  
308 pre-trained models (Dermouche and Pelachaud, 2019; Wang et al., 2019) to extract high-level features  
309 about the user, such as their level of engagement.

310 2. *Dialog Model*. In this module the dialog manager Flipper (van Waterschoot et al., 2018) selects the  
311 dialog act that the agent will perform, as well as the communicative intention of the agent (i.e., how to  
312 perform that dialog act).

313 3. *Agent's Behaviour*. Agent's behaviour generation is performed by GRETA, a software platform  
314 supporting the creation of socio-emotional embodied conversational agents (Pecune et al., 2014).  
315 The *Agent's Behaviour* module is made of two main modules: the Behaviour Planner receives the  
316 communicative intentions of the ECA from the *Dialog Model* module as input and instantiates them  
317 into multi-modal behaviours; the Behaviour Realiser transforms the multi-modal behaviours into facial  
318 and body animations to be displayed on a graphics screen.

319 4. *Adaptation Mechanism*. Since the ECA can adapt its behaviours at different levels, the *Adaptation*  
320 *Mechanism* module is implemented in different parts of the architecture, according to the type of  
321 adaptation the ECA performs. That is, the adaptation can affect the communicative intentions of the  
322 ECA or it can occur during the behaviour realisation at the animation level. In the first two models  
323 presented in this paper, the *Adaptation Mechanism* module is connected to the *Dialog Model* module,  
324 while for the third model it is connected to the *Agent's Behaviour* module.

## 6 SCENARIO

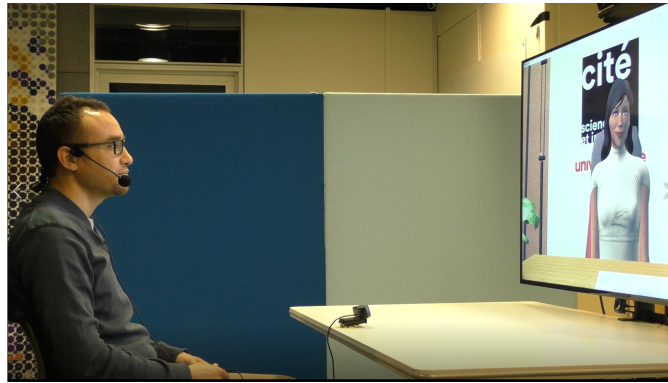
325 Each type of adaptation has been investigated by running human-agent interaction experiments at the  
326 Science Museum of Paris. In the scenario conceived for these experiments, the ECA, called Alice, played  
327 the role of a virtual guide of the museum.

328 The experiment room included a questionnaires space, including a desk with a laptop and a chair; an  
329 interaction space, with a big TV screen displaying the ECA, a Kinect 2 placed on the top of the TV screen  
330 and a black tent behind the chair where the participant sat; a control space, separated from the rest of the  
331 room by 2 screens, including a desk with the computer running the system architecture. The interaction  
332 space is shown in Figure 2.

333 The experiments were completed in three phases:

- 334 1. Before the interaction began, the participant sat at the questionnaires space, read and signed the consent  
335 form, and filled out a first questionnaire (*NARS*, see below). Then they moved to the interaction space,  
336 where the experimenter gave the last instructions [5 min];
- 337 2. During the interaction phase, the participant stayed right in front of the TV screen, between it and the  
338 black tent. They wore a headset and was free to interact with the ECA as they wanted. During this  
339 phase, the experimenter stayed in the control space, behind the screens [3 min];
- 340 3. After the interaction, the participant came back to the questionnaires space and filled out the last  
341 questionnaires about their perception of the ECA and of the interaction. After that, the experimenter  
342 proceeded with the debriefing [5 min].

343 Before the interaction with the ECA, we asked participants to fill out a questionnaire about their a-priori  
344 about virtual characters (*NARS*): an adapted version of *NARS* scale from Nomura et al. (2006) was used.  
345 Items of the questionnaire included for example how much participants would feel relaxed talking with a  
346 virtual agent, or how much they would like the idea that virtual agents made judgements.



**Figure 2.** The interaction space in the experiment room. The participants were sitting in front of the TV screen displaying the ECA. On the left, 2 screens separated the interaction space from the control space.

347 The interaction with the ECA lasted about 3 minutes. It included 26 steps. A step included one dialog act  
348 played by the ECA and participant's potential reaction/answer. The dialog scenario was built so the ECA  
349 drove the discussion. The virtual guide provided information on an exhibit that was currently happening  
350 in the museum. It also asked some questions about participants' preferences. Purposely, we limited the  
351 possibility for participants to take the lead of the conversation as we wanted to avoid any error due to  
352 automatic speech understanding. [More details about the dialog model can be found in \(Biancardi et al.,](#)  
353 [2019a\).](#)

## 7 STUDY 1: ADAPTATION OF AGENT'S BEHAVIOURS

354 At this step we aim to investigate adaptation at a high level, meant as convergence of the agent's behaviours  
355 according to user's impressions of the ECA.

356 The goal of this first model is to make the ECA learn the verbal and non-verbal behaviours to be perceived  
357 as warm or competent by measuring and using user's impressions as reward.

### 358 7.1 Architecture

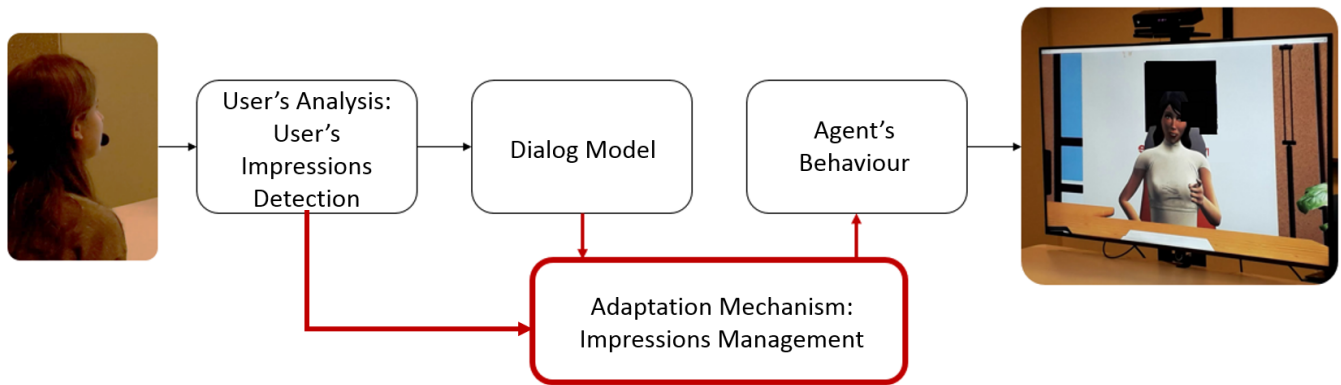
359 The general architecture described in Section 5 has been modified in order to contain a module for the  
360 detection of user's impressions, and a specific set of verbal and non-verbal behaviours from which the ECA  
361 could choose.

362 The modified architecture of the system is depicted in Figure 3. In the following Section we give more  
363 details about the modified modules.

#### 364 7.1.1 User's Analysis: User's Impressions Detection

365 User's impressions can be detected from their non-verbal behaviours, in particular their facial expressions.  
366 The *User's Analysis* module is integrated with a *User's Impressions Detection* module that takes as input a  
367 stream of user's facial Action Units (AUs) (Ekman et al., 2002) and outputs the potential user's impressions  
368 about the level of warmth (or competence) of the ECA.

369 A trained Multilayer Perceptron Regression (MLP) model is implemented in this module to detect the  
370 impressions formed by users' about the ECA. The MLP model was previously trained with a corpus  
371 including face video recordings and continuous self-report annotations of [warmth and competence](#) given  
372 by participants watching the videos of the NoXi database (Cafaro et al., 2017). The self-report annotations  
373 being considered separately, the MLP model was trained twice, one for warmth and one for competence.  
374 More details about this model can be found in (Wang et al., 2019).



**Figure 3.** The modified system architecture used in Study 1. In particular, the *User's Analysis* module contains the model to detect user's impressions from facial signals. The *Impressions Management* module contains the Q-learning algorithm.

### 375 7.1.2 Adaptation Mechanism: Impressions Management.

376 In this model the adaptation of the ECA concerns the impressions of **warmth and competence** given to  
 377 the user. The inputs of the *Adaptation Mechanism* module are the dialog act to be realised (coming from  
 378 the *Dialog Model* module) and the user's impression of agent's warmth or competence (coming from the  
 379 *User's Analysis* module). The output is a combination of behaviours to realise the dialog act, chosen from a  
 380 set of possible verbal and non-verbal behaviours to perform.

381 To be able to change the agent's behaviour according to detected participant's impressions, a machine  
 382 learning algorithm is applied. We follow a reinforcement learning approach to learn which actions the  
 383 ECA should take (here verbal and non-verbal behaviours) in response to some events (here user's detected  
 384 impressions). We rely on a Q-learning algorithm for this step. More details about it can be found in  
 385 (Biancardi et al., 2019b).

386 The set of verbal and non-verbal behaviours, from which the Q-learning algorithm selects a combination  
 387 to send to the Behaviour Planner of the *Agent's Behaviour* module, includes:

- 388 • *Type of gestures.* The ECA could perform *ideational* (i.e., related to the content of the speech) or *beat*  
 389 (i.e., marking speech rhythm, not related to the content of the speech) gestures or *no gestures*.
- 390 • *Arms rest poses:* in the absence of any kind of gesture, these rest poses could be performed by the ECA:  
 391 *akimbo* (i.e., hands on the hips), *arms crossed* on the chest, *arms along* its body, or *hands crossed* on  
 392 the table.
- 393 • *Smiling.* During the animation, the ECA could decide whether or not to perform smiling behaviour,  
 394 characterised by the activation of AU6 (cheek raiser) and AU12 (lip puller up).
- 395 • *Verbal behaviour.* The ECA could modify the use of *you-* and *we-*words, the level of formality of  
 396 the language, the length of the sentences. These features have been found to be related to different  
 397 impressions of **warmth and competence** (Pennebaker, 2011; Callejas et al., 2014).

## 398 7.2 Experimental Design

399 The adaptation model described in the previous Subsection 7.1.2 has been evaluated by using the scenario  
 400 described in Section 6. Here we describe the experimental variables manipulated and measured during the  
 401 experiment.

### 402 7.2.1 Independent Variable.

403 The independent variable manipulated in this experiment, called *Model*, concerns the use of the adaption  
404 model and includes 3 conditions:

- 405 • *Warmth*, when the ECA adapts its behaviours according to user's impressions of agent's warmth, with  
406 the goal to maximise these impressions;
- 407 • *Competence*, when the ECA adapts its behaviours according to user's impressions of the agent's  
408 competence, with the goal to maximise these impressions;
- 409 • *Random*, when the adaptation model is not exploited and the ECA randomly chooses its behaviour,  
410 without considering user's reactions.

### 411 7.2.2 Measures.

412 The dependent variables measured after the interaction with the ECA are:

- 413 • User's perception of agent's warmth (*w*) and competence (*c*): participants were asked to rate their level  
414 of agreement about how well each adjective described the ECA (4 adjectives concerning warmth, 4  
415 concerning competence, according to Aragonés et al. (2015)). Even though only one dimension was  
416 manipulated at a time, we measured user's impressions about both of them in order to check whether  
417 the manipulation of one dimension can affect the impressions about the other (as already found in  
418 literature (Rosenberg et al., 1968; Yzerbyt et al., 2005; Judd et al., 2005)).
- 419 • User's experience of the interaction (*exp*): participants were asked to rate their level of agreement  
420 about a list of items adapted from (Bickmore et al., 2011).

### 421 7.2.3 Hypotheses.

422 We hypothesised that:

423 **H1:** When the ECA is in the *Warmth* condition, that is, when it adapts its behaviours according to user's  
424 impressions of agent's warmth, it will be perceived as *warmer* compared to the *Random* condition;

425 **H2:** When the ECA is in the *Competence* condition, that is, when it adapts its behaviours according to  
426 user's impressions of agent's competence, it will be perceived as *more competent* compared to the *Random*  
427 condition;

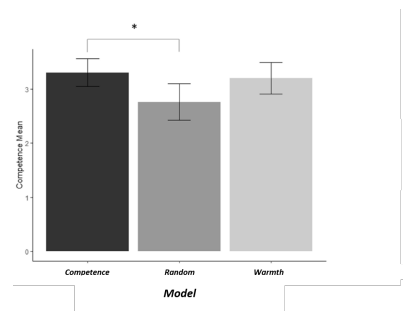
428 **H3:** When the agent ECA its behaviours, that is, in either *Warmth* or *Competence* conditions, this will  
429 improve user's experience of the interaction, compared to the *Random* condition.

## 430 7.3 Analysis and Results

431 The visitors (24 women and 47 men) of the Carrefour Numérique of the Cité des sciences et de l'industrie  
432 of Paris were invited to take part in our experiment. 28% of them were in the range 18-25 years old, 18%  
433 were in the range 25-36, 28% in the range 36-45, 15% in the range of 46-55 and 11% were over 55 years  
434 old. Participants were randomly assigned to each condition with 25 participants assigned to the *Warmth*  
435 condition, 27 to the *Competence* condition and 19 to the *Random* one.

436 We computed Cronbach's alphas on the scores of the 4 items about *w* and the 4 about *c*: good reliability  
437 was found for both ( $\alpha = 0.85$  and  $\alpha = 0.81$  respectively). Then, we computed the mean of these items in  
438 order to have one *w* score and one *c* score for each participant and we used them for our analyses.

439 Since *NARS* scores got an acceptable degree of reliability ( $\alpha = 0.69$ ), we computed the overall mean of  
440 these items for each participant and divided them into 2 groups, "high" and "low", according to whether  
441 they obtained a score higher than the overall mean or not, respectively. Participants were almost equally  
442 distributed into the two groups (35 in the "high" group, 36 in the "low" group). Chi-square tests for *Model*,



**Figure 4.** Competence means for each level of *Model*. \* stands for  $p < 0.05$ .

443 age and sex were run to verify that participants were equally distributed across these variables, too (all  
444  $p > 0.5$ ).

#### 445 7.3.1 Warmth Scores.

446 The  $w$  means were normally distributed (Shapiro test's  $p = 0.07$ ) and their variances homogeneous  
447 (Bartlett tests'  $ps$  for each variable were  $> 0.44$ ). We run a  $3 \times 5 \times 2 \times 2$  between-subjects ANOVA, with  
448 *Model*, age, sex and *NARS* as factors.

449 No effects of age or sex were found. A main effect of *NARS* was found ( $F(1, 32) = 4.23, p < 0.05$ ). A  
450 post-hoc test specified that the group who got high scores in *NARS* gave higher ratings about the agent's  $w$   
451 ( $M = 3.65, SD = 0.84$ ) than the group who got low scores in *NARS* ( $M = 3.24, SD = 0.96$ ).

452 Although we did not find any significant effect,  $w$  scores were on average higher in the *Warmth* and  
453 *Competence* conditions than in the *Random* condition. Mean and standard error of  $w$  scores are shown in  
454 Table 1.

<i>Model</i>	Warmth $\mu \pm SD$	Competence $\mu \pm SD$
<i>Warmth</i>	$3.48 \pm 0.8$	$3.2 \pm 0.75$
<i>Competence</i>	$3.51 \pm 0.96$	$3.3 \pm 0.69$
<i>Random</i>	$3.26 \pm 0.93$	$2.76 \pm 0.73$

**Table 1.** Mean and standard deviation of  $w$  and  $c$  scores for each level of *Model*.

#### 455 7.3.2 Competence Scores.

456 The  $c$  means were normally distributed (Shapiro test's  $p = 0.22$ ) and their variances homogeneous  
457 (Bartlett tests'  $ps$  for each variable were  $> 0.25$ ). We run a  $3 \times 5 \times 2 \times 2$  between-subjects ANOVA, with  
458 *Model*, age, sex and *NARS* scores as factors.

459 We did not find any effect of age, sex or *NARS*. A significant main effect of *Model* was found ( $F(2, 32) =$   
460  $3.22, p = 0.047, \eta^2 = 0.085$ ). In particular, post-hoc tests revealed that participants in the *Competence*  
461 condition gave higher scores about the agent's  $c$  than participants in the *Random* condition ( $M_C =$   
462  $3.3, M_R = 2.76, p\text{-adj} = 0.05$ ).

#### 463 7.3.3 User's experience Scores.

464 The *exp* items' means were not normally distributed but their variances were homogeneous (Bartlett tests'  
465  $ps$  for each variable were  $> 0.17$ ). We run non-parametric tests for each item and each variable.

466 Even if we did not find any statistically significant effect, on average items' scores tended to be higher in  
467 *Warmth* and *Competence* conditions than in *Random* condition.

468 7.3.4 Performance of the adaptation model.

469 The Q-learning algorithm ended up selecting (for each participant) one specific combination of verbal  
470 and non-verbal behaviours from the  $84\% \pm 7$  and  $82\% \pm 7$  of the interaction, for *Warmth* and *Competence*  
471 conditions respectively. In the *Warmth* condition the rest pose *Akimbo* was the most selected one ( $\chi^2 =$   
472  $8.05, p < 0.01$ ), and we found a tendency to use *Ideational* gestures ( $p > 0.05$ ). In the *Competence*  
473 condition the *Verbal Behaviour* aiming at eliciting low warmth and high competence (formal language,  
474 long sentences, use of *you*-words) was the most selected one ( $\chi^2 = 3.86, p < 0.01$ ).

#### 475 7.4 Discussion

476 The results show that participants' ratings tended to be higher in the conditions in which the ECA used the  
477 adaptation model, compared to when it selected its behaviour randomly. In particular, the results indicate  
478 that we successfully manipulated the impression of competence when using our adaptive ECA. Indeed,  
479 higher competence was reported in the *Competence* condition compared to the *Random* one. No a-priori  
480 effect was found.

481 On the other hand, we found an a-priori effect on warmth but no significant effect of our conditions (just  
482 a positive trend for both *Competence* and *Warmth* conditions). People with high a-priori about virtual  
483 agents gave higher ratings about the agent's warmth than people with low a-priori.

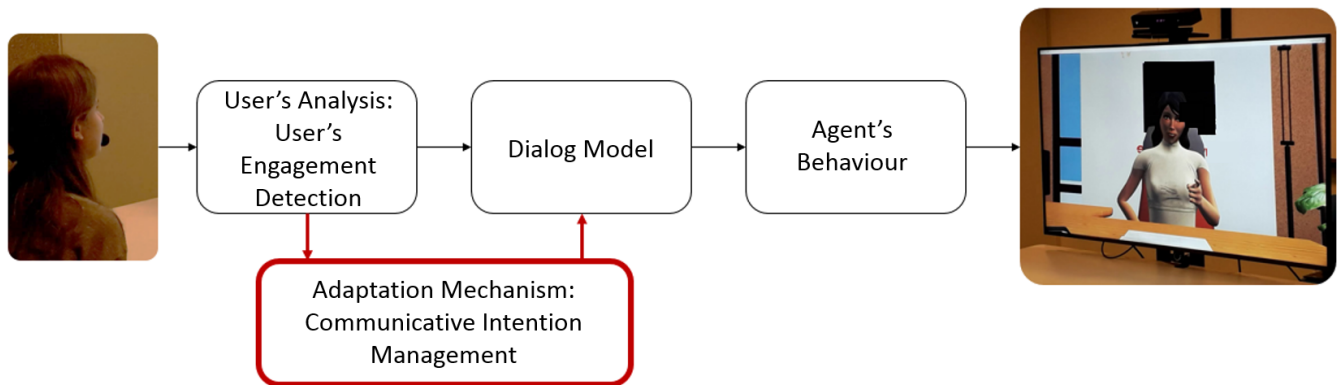
484 We could hypothesise some explanations for these results. First, we did not get effects of our experimental  
485 conditions on warmth ratings since people were more anchored into their a-priori and it was hard to change  
486 them. Indeed, people's expectancies have already been found to have an effect on user's judgements about  
487 ECAs (Burgoon et al., 2016; Biancardi et al., 2017b; Weber et al., 2018). The fact that we found this  
488 effect only for warmth judgements could be related to the primacy of warmth judgements over competence  
489 (Wojciszke and Abele, 2008). Then, it could have been easier to elicit impressions of competence since we  
490 found no a-priori effect on competence. This could be explained as people might expect that it is easier to  
491 implement knowledge in an ECA rather than social behaviours.

492 User's experience of the interaction was not affected by agent's adaption. During the debriefing many  
493 participants expressed their disappointment about the agent's appearance, the quality of the voice synthesizer  
494 and the animation, described as "disturbing", "creepy", as well as the limitations of the conversation  
495 (participants could only answer to ECA's questions). These factors could have reduced any other effect of  
496 the independent variables. Indeed, the agent's appearance and the structure of the dialog were the same  
497 across conditions. If participants mainly focused on these elements, they could have paid less attention to  
498 ECA's verbal and non-verbal behaviour (the variables that were manipulated and we were interested in),  
499 which thus did not manage to affect their overall experience of the interaction.

## 8 STUDY 2: ADAPTATION OF COMMUNICATIVE STRATEGIES

500 At this step we investigate adaptation at a higher level than the previous one, namely the communicative  
501 strategies of the ECA. In particular, we focus on the agent's self-presentational strategies, that is, different  
502 techniques to convey different levels of *warmth and competence* towards the user (Jones and Pittman,  
503 1982). Each strategy is realised in terms of the verbal and non-verbal behaviour of the ECA, according to  
504 (Biancardi et al., 2017a; Callejas et al., 2014; Pennebaker, 2011).

505 While in the previous study we investigated whether and how adaptation could affect user's impressions  
506 of the agent, we here focus on whether and how adaptation can affect user's engagement during the  
507 interaction.



**Figure 5.** The modified system architecture used in Study 2. In particular, the *User's Analysis* Module contains the model to detect user's engagement from facial and head/trunk signals. The *Communicative Intention* module uses reinforcement learning to select the agent's self-presentational strategy.

508 The goal of this second model is thus to make the ECA learn the communicative strategies that improve  
 509 user's engagement, by measuring and using user's engagement as reward.

### 510 8.1 Architecture

511 The general architecture described in Section 5 has been modified in order to contain a module for  
 512 the detection of user's engagement, and a communicative intention planner for the choice of the agent's  
 513 self-presentational strategy.

514 The modified architecture of the system is depicted in Figure 5. In the following subsection we give more  
 515 details about the modified modules.

#### 516 8.1.1 User's Analysis: User's Engagement Detection.

517 The *User's Analysis* module is integrated with a *User's Engagement Detection* module that continuously  
 518 computes the overall user's engagement at the end of every speaking turn. The computational model of  
 519 user's engagement is based on the detection of facial signals and head/trunk signals, that are indicators  
 520 of engagement. In particular, smiling is usually considered an indicator of engagement, as it may show  
 521 that the user is enjoying the interaction (Castellano et al., 2009). Eyebrows are equally important: for  
 522 example, Corrigan et al. (2016) claimed that "frowning may indicate effortful processing suggesting high  
 523 levels of cognitive engagement". Head/trunk signals are detected in order to measure user's attention level.  
 524 According to Corrigan et al. (2016), attention is a key aspect of engagement: an engaged user continuously  
 525 gazes at relevant objects/persons during the interaction. We approximate user's gaze with the user's head  
 526 and trunk orientation.

#### 527 8.1.2 Adaptation Mechanism: Communicative Intention Management.

528 During its interaction with the user, the agent has the goal of selecting its *self-presentational strategy*  
 529 (e.g., to communicate verbally and non-verbally a given dialog act with high warmth and low competence).  
 530 The agent can choose its strategy among a given set of 4 strategies inspired from Jones and Pittman's  
 531 taxonomy (Jones and Pittman, 1982):

- 532 • *Ingratiation*: the ECA has the goal to convey positive interpersonal qualities and elicit impressions of  
 533 high warmth towards the user, without considering its level of competence;
- 534 • *Supplication*: the ECA has the goal to present its weaknesses and elicit impressions of high warmth  
 535 and low competence;



- 536 • *Self-promotion*: the ECA has the goal to focus on its capabilities and elicit impressions of high  
537 competence, without considering its level of warmth;
- 538 • *Intimidation*: the ECA has the goal to elicit impressions of high competence by decreasing its level of  
539 warmth.

540 The verbal behaviour characterising the different strategies is inspired from the works of Pennebaker (2011)  
541 and Callejas et al. (2014). In particular, we took into account the use of *you*- and *we*-words, the level of  
542 formality of the language, the length of the sentences.

543 The choice of agent's non-verbal behaviour is based on our previous studies described in (Biancardi et al.,  
544 2017a,b). So, for example, if the current agent's self-presentational strategy is *Supplication* and the next  
545 dialog act to be spoken is introducing a topic, then the agent would say "I think that while you play there  
546 are captors that measure tons of stuffs!" accompanied by smiling and beat gestures. Conversely, if the  
547 current agent's self-presentational strategy is *Intimidation* and the next dialog act to be spoken is the same,  
548 then the agent would say "While you play at video games, several captors measure your physiological  
549 signals." accompanied by ideational gestures without smiling.

550 To be able to change the agent's communicative strategy according to the detected participant's  
551 engagement, we applied a reinforcement learning algorithm to make the ECA learn what strategy to  
552 use. Specifically, a multi-armed bandit algorithm (Katehakis and Veinott Jr, 1987) was applied. This  
553 algorithm is a simplified setting of reinforcement learning which models agents evolving in an environment  
554 where they can perform several actions, each action being more or less rewarding for them. The choice of  
555 the action does not affect the state (i.e., what happens in the environment). In our case, the *actions* that  
556 the ECA could perform are the verbal and non-verbal behaviours corresponding to the self-presentational  
557 strategy the ECA aims to communicate. The *environment* is the interaction with the user, while the *state*  
558 space is the set of dialog acts used at each speaking turn. The choice of the *action* does not change the *state*  
559 (i.e., the dialog act used during the actual speaking turn), but rather it acts on how this dialog act is realised  
560 by verbal and non-verbal behaviour. More details about the multi-armed bandit function used in our model  
561 can be found in (Biancardi et al., 2019a).

## 562 8.2 Experimental Design

563 The adaptation model described in the previous Section 8.1.2 was evaluated by using the scenario  
564 described in Section 6. Here we describe the experimental variables manipulated and measured during the  
565 experiment.

### 566 8.2.1 Independent Variable.

567 The design includes one independent variable, called *Communicative Strategy*, with 6 levels determining  
568 the way the ECA chooses the strategy to use:

- 569 1. *Adaptation*: the ECA uses the adaptation model and thus selects one self-presentational strategy at  
570 each speaking turn, by using user's engagement as reward;
- 571 2. *Random*: the ECA chooses a random behaviour at each speaking turn;
- 572 3. *Ingr\_static*: the ECA always adopts the *Ingratiation* strategy during the whole interaction;
- 573 4. *Suppl\_static*: the ECA always adopts the *Supplication* strategy during the whole interaction;
- 574 5. *Self\_static*: the ECA always adopts the *Self-promotion* strategy during the whole interaction;
- 575 6. *Intim\_static*: the ECA always adopts the *Intimidation* strategy during the whole interaction.

## 576 8.2.2 Measures.

577 The dependent variables measured after the interaction with the ECA are the same described in subsection  
578 7.2.2.

579 In addition to these measures, during the interaction, for people who agreed with audio recording of the  
580 experiment, we collected quantitative information about their verbal engagement, in particular: the polarity  
581 of user's answer when the ECA asked if they wanted to continue to discuss; the number of any verbal  
582 feedback produced by the user during a speaking turn.

## 583 8.2.3 Hypotheses.

584 We hypothesised that each self-presentational strategy would elicit the right degree of **warmth and**  
585 **competence**, in particular:

586 **H1ingr**: The ECA in *Ingr.static* condition would be perceived as *warm* by users;

587 **H1supp**: The ECA in *Suppl.static* condition would be perceived as *warm* and *not competent* by users;

588 **H1self**: The ECA in *Self.static* condition would be perceived as *competent* by users;

589 **H1intim**: The ECA in *Intim.static* condition would be perceived as *competent* and *not warm* by users.

590 Then, we hypothesised that:

591 **H2a**: An ECA adapting its self-presentational strategies according to user's engagement would improve  
592 user's experience, compared to a non-adapting ECA;

593 **H2b**: The ECA in *Adaptation* condition would influence how it is perceived in terms of **warmth and**  
594 **competence**.

## 595 8.3 Analysis and Results

596 75 participants (30 females) took part in the evaluation, equally distributed among the 6 conditions. The  
597 majority of them were in the 18-25 or 36-45 age range and were native French speakers. In this section we  
598 briefly report the main results of our analyses. A more detailed report can be found in (Biancardi et al.,  
599 2019a).

### 600 8.3.1 Warmth Scores.

601 A 4x2 between-subjects ANOVA revealed a main effect of the **Communicative Strategy** ( $F(5, 62) = 4.75$ ,  
602  $p < 0.001$ ,  $\eta^2 = 0.26$ ) and **NARS** ( $F(1, 62) = 5.74$ ,  $p < 0.05$ ,  $\eta^2 = 0.06$ ). The  $w$  ratings were higher from  
603 participants with a high NARS score ( $M = 3.74$ ,  $SD = 0.77$ ) than from those with a low NARS score  
604 ( $M = 3.33$ ,  $SD = 0.92$ ).

605 Table 2 shows mean and SD of  $w$  scores for each level of **Communicative Strategy**. Multiple comparisons  
606 t-test using Holm's correction show that the  $w$  mean for *Intim.static* is significantly lower than all the  
607 others (see Table 2). As consequence, the other conditions are rated as warmer than *Intim.static*. **H1ingr**,  
608 **H1supp** are thus validated, and **H1intim** and **H2b** are validated for the warmth component.

### 609 8.3.2 Competence Scores.

610 No significant results emerged from the analyses. When looking at the means of  $c$  for each condition (see  
611 Table 3), *Suppl.static* is the one with the lower score, even if its difference with the other scores does not  
612 reach statistical significance (all  $p$ -values  $> 0.1$ ). **H1supp** and **H1intim** (for the competence component)  
613 are not validated.

### 614 8.3.3 User's experience of the interaction

615 Participants in the *Ingr.static* condition were more satisfied from the interaction than those in *Suppl.static*  
616 ( $z = 2.88$ ,  $p\text{-adj} < 0.05$ ) and in *Intim.static* ( $z = 2.56$ ,  $p\text{-adj} < 0.05$ ). Participants in the *Ingr.static*

Communicative Strategy	Warmth $\mu \pm$ SD
<i>Ingr_static</i>	3.77 $\pm$ 0.57
<i>Supp_static</i>	3.54 $\pm$ 0.999
<i>Self_static</i>	3.81 $\pm$ 0.70
<i>Intim_static</i>	2.63 $\pm$ 0.93
<i>Random</i>	3.71 $\pm$ 0.80
<i>Adaptation</i>	3.89 $\pm$ 0.38

**Table 2.** Mean and SD values of warmth scores for each level of *Communicative Strategy*.

Communicative Strategy	Competence $\mu \pm$ SD
<i>Ingr_static</i>	3.6 $\pm$ 0.62
<i>Supp_static</i>	2.98 $\pm$ 0.77
<i>Self_static</i>	3.75 $\pm$ 0.63
<i>Intim_static</i>	3.65 $\pm$ 0.79
<i>Random</i>	3.5 $\pm$ 0.70
<i>Adaptation</i>	3.43 $\pm$ 0.76

**Table 3.** Mean and SD values of competence scores for each level of *Communicative Strategy*. No significant differences among the conditions were found.

617 condition also liked the ECA more than participants in the *Intim\_static* condition ( $z = 2.87$ ,  $p\text{-adj} < 0.05$ ).  
 618 No differences were found between the scores of the participants in the *Adaptation* condition and those of  
 619 the other participants, for any of the items measuring *exp*.

620 The *exp* scores are also affected by participants' a-priori about virtual agents (measured through the  
 621 *NARS* questionnaire). In particular, participants who got high scores in the *NARS* questionnaire were  
 622 more satisfied by the interaction ( $U = 910.5$ ,  $p < 0.05$ ), were more motivated to continue the interaction  
 623 ( $U = 998$ ,  $p = 0.001$ ) and perceived the agent as less closed to a computer ( $U = 1028$ ,  $p < 0.001$ ) than  
 624 people who got low scores in the *NARS* questionnaire.

625 Another interesting result concerns the effect of age on participants' satisfaction ( $H(4) = 15.05$ ,  $p <$   
 626  $0.01$ ): people in the age range 55+ were more satisfied than people of any other age range (all  $p\text{-adj} < 0.05$ ).

627 On the whole, these results do not allow us to validate **H2a**, but agent's adaptation was found to have at  
 628 least an effect on its level of warmth (**H2b**).

#### 629 8.3.4 Verbal cues of engagement

630 During each speaking turn, the user was free to reply to the agent's utterances. We consider as a user's  
 631 verbal feedback any type of verbal reply to the ECA, from a simple backchannel (e.g., "ok", "mm") to a  
 632 longer response (e.g., giving an opinion about what the ECA said). In general, participants who did not  
 633 give much verbal feedback (i.e., less than 13 replies to the agent's utterances over all the speaking turns)  
 634 answered positively to the ECA when it asked whether they wanted to continue to discuss with it, compared  
 635 to the participants who gave more verbal feedback ( $OR = 4.27$ ,  $p < 0.05$ ). In addition, we found that the  
 636 participants who did not give much verbal feedback liked the ECA more compared to those who talked a  
 637 lot during the interaction ( $U = 36.5$ ,  $p < 0.05$ ). However, no differences in any of the dependent variables  
 638 were found according to *Communicative Strategy*.

### 639 8.4 Discussion

640 First of all, regarding **H1**, the only statistically significant results concern the perception of agent's warmth.  
 641 The ECA was rated as colder when it adopted *Intim\_static* strategy, compared to the other conditions. This  
 642 supports the thesis of the primacy of warmth dimension (Wojciszke and Abele, 2008) and it is in line

643 with the positive-negative asymmetry effect described by (Peeters and Czapinski, 1990), who argues that  
644 negative information has generally a higher impact in person perception than positive information. In our  
645 case, when the ECA displayed cold (i.e., low warmth) behaviours (i.e., in **Intim\_static** condition), it was  
646 judged by participants with statistically significant lower ratings of warmth. Regarding the other conditions  
647 (**Ingr\_static**, **Supp\_static**, **Self\_static**, **Adaptation** and **Random**), they elicited warmer impressions in the  
648 user, but there was not one strategy better than the others in this regard. The fact that also the **Self\_static**  
649 elicited the same level of warmth than the others could reflect an halo effect (Rosenberg et al., 1968): the  
650 behaviours displayed to appear competent influenced its warmth perception in the same direction.

651 Regarding **H2**, the results do not validate our hypothesis **H2a** that the interaction would be improved  
652 when the ECA managed its impressions by adapting its strategy according to user's engagement. When  
653 analysing scores for *exp* items, we found that participants were more satisfied by the interaction and  
654 they liked the ECA more when the ECA wanted to be perceived as warm (i.e., in **Ingr\_static** condition),  
655 compared to when it wanted to be perceived as cold and competent (i.e., in **Intim\_static** condition). An  
656 hypothesis is that, since the ECA was perceived warmer in **Ingr\_static** condition, it could have positively  
657 influenced the ratings of the other items, like user's satisfaction. Concerning **H2b** about a possible effect of  
658 agent's adaptation on user's perception of its **warmth and competence**, it is interesting to see that when  
659 the ECA adapted its self-presentational strategy according to user's overall engagement, it was perceived  
660 as warm. This highlights a link between agent's adaptation, user's engagement and warm impression: the  
661 more the ECA adapted its behaviours, the more the user was engaged and the more she/he perceived the  
662 ECA as warm.

## 9 STUDY 3: ADAPTATION AT A SIGNAL LEVEL

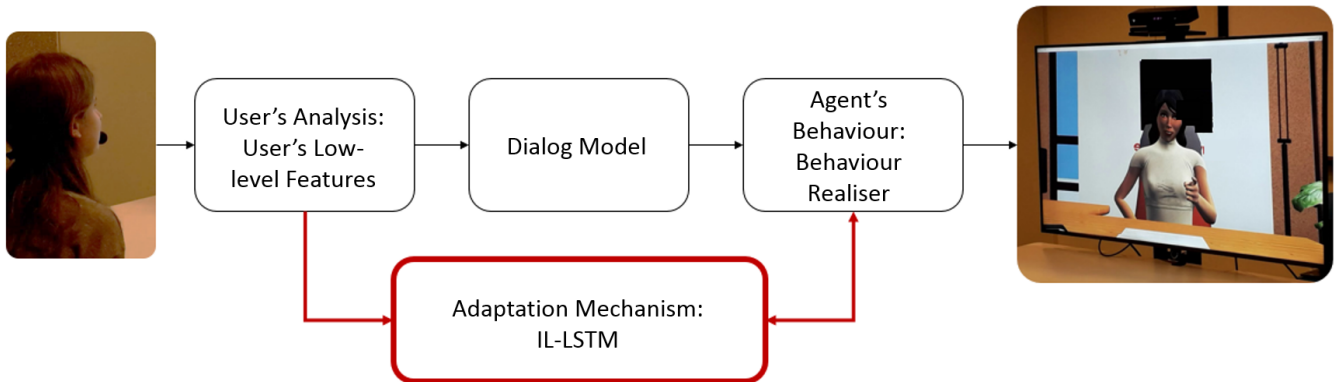
663 At this step, we are interested in low-level adaptation at the signal level. We aim to model how the ECA  
664 can adapt its signals to user's signals. Thus, we make the ECA predict the signals to display at each time  
665 step, according to those displayed by both the ECA and the user during a given time window. For sake of  
666 simplicity, we consider a subset of signals, namely lip corners movement (AU12), gaze direction and head  
667 movement. To reach our aim, we follow a two-steps approach. At first, we need to predict which signals  
668 due to adaptation to user's behaviours should be displayed by the ECA at each time step. The prediction of  
669 signals adaptation is learned on human-human interaction. The ECA ought to communicate its intentions as  
670 well as to adapt to user's signals. Then, the second step of our approach consists in blending the predicted  
671 signals linked to the adaptation mechanism with the non-verbal behaviours corresponding to the agent's  
672 communicative intentions. We describe in further details our algorithm in subsection 9.1.2.

### 673 9.1 Architecture

674 The general architecture described in Section 5 has been modified in order to contain a module for  
675 predicting the next social signal to be merged with the agent's other communicative ones. The modified  
676 architecture of the system is depicted in Figure 6. In the following we explain the modified modules. More  
677 details about these modules can be found in (Dermouche and Pelachaud, 2019).

#### 678 9.1.1 User's Analysis: User's Low-level features

679 Low-level features of the user are obtained from the *User's Analysis* module using EyesWeb of the  
680 general architecture. In this model, we consider a subset of these features, namely: user's head direction,  
681 user's eyes direction and AU12 (upper lip corner activity). At every frame, the EyesWeb module extracts  
682 these features and sends the last 20 analysed frames to the *Adaptation Mechanism* module *IL-LSTM* (see  
683 Section 9.1.2). It also sends user's conversational state (speaking or not) computed from the detection of



**Figure 6.** The modified system architecture used in Study 3. In particular, the *User's Analysis* module detects user's low-level signals such as head and eyes rotations and lip corners activity. The *Adaptation Mechanism* module exploits the *IL-LSTM* model for selecting the agent's low-level signals. In the *Agent's Behaviour* module, the Behaviour Realiser is customised in order to take into account the agent's communicative behaviours and signals coming from the *IL-LSTM* module in real-time.

684 user's voice activity (done in EyesWeb) and from the agent-turn information provided by the dialogue

685 manager Flipper.

### 686 9.1.2 Adaptation Mechanism: Interaction Loop-LSTM

687 In this version of the architecture, the adaptation mechanism is based on a predictive model trained on  
 688 data of human-human interactions. We used the NoXi database (Cafaro et al., 2017) to train an Long  
 689 Short-Term Memory LSTM model that takes as input sequences of signals of two interactants over a sliding  
 690 window of  $n$  frames to predict which signal(s) should display one participant at time  $n+1$ . We call this  
 691 model *IL-LSTM*, that stands for Interaction Loop-LSTM. LSTM is a kind of Recurrent Neural Networks. It  
 692 is mainly used when "context" is important, i.e., decisions from the past can influence the current ones. It  
 693 allows us to model both sequentiality and temporality of non-verbal behaviours.

694 We apply *IL-LSTM* model to the human-agent interaction. Thus, given the signals produced by both, the  
 695 human and the ECA, over a time window, the model outputs which signals should display the ECA at  
 696 the next time step (here a frame). The predicted signals are sent to the Behaviour Realiser of the *Agent's*  
 697 *Behaviour* module where they are merged with the behaviours of the ECA related to its communicative  
 698 intents.

### 699 9.1.3 Agent's Behaviour: Behaviour Realiser

700 We have updated the Behaviour Realiser so the ECA not only communicates its intentions but also adapts  
 701 its behaviours in real time to user's behaviours. This module blends the predicted signals linked to the  
 702 adaptation mechanism with the non-verbal behaviours corresponding to its communicative intentions that  
 703 have been outputted using the GRETA agent platform (Pecune et al., 2014). More precisely, the dialogue  
 704 module Flipper sends the set of communicative intentions to the *Agent's Behaviour* module. This module  
 705 computes the multi-modal behaviour of the ECA and sends it to the Behaviour Realiser that computes the  
 706 animation of the ECA's face and body. Then, before sending each frame to be displayed by the animation  
 707 player, the animation computed from the communicative intentions is merged with the animation predicted  
 708 by the *Adaption Mechanism* module. This operation is repeated at every frame.

## 709 9.2 Experimental Design

710 The adaptation model described in the previous Section was evaluated by using the scenario described in  
711 Section 6. Here we describe the experimental variables manipulated and measured during the experiment.

### 712 9.2.1 Independent Variable.

713 We manipulated the type of *Low-level adaptation* of the ECA by considering five conditions:

- 714 • **Random**: when the ECA did not adapt its behaviour;
- 715 • **Head**: when the ECA adapted its head rotation according to the user's behaviour;
- 716 • **Lip Corners**: when the ECA adapted its lip corners puller movement (AU12) according to the user's  
717 behaviour;
- 718 • **Eyes**: when the ECA adapted its eyes rotation according to the user's behaviour;
- 719 • **All**: when the ECA adapted its head and eyes rotation and lip corners movement, according to the  
720 user's behaviour.

721 We tested these five conditions with a between-subjects design.

### 722 9.2.2 Measures.

723 The dependent variables measured after the interaction with the ECA were user's engagement and the  
724 perceived friendliness of the ECA.

725 User's engagement was evaluated using the I-PEFiC framework (van Vugt et al., 2006) that encompasses  
726 user's engagement and satisfaction during human-agent interaction. This framework considers different  
727 dimensions regarding the perception of the ECA (in terms of *realism*, *competence* and *relevance*) as well  
728 as user's engagement (*involvement* and *distance*) and user's *satisfaction*. We adapted the questionnaire  
729 proposed by Van Vugt and colleagues to measure the behaviour of the ECA along these dimensions (van  
730 Vugt et al., 2006). The perceived *friendliness* of the ECA was measured through the adjectives *kind*, *warm*,  
731 *agreeable* and *sympathetic* of the IAS questionnaire (Wiggins, 1979).

732 As for the other two studies, we also measured the a-priori attitude of participants towards virtual agents  
733 through the *NARS* questionnaire.

### 734 9.2.3 Hypotheses.

735 Previous studies (Liu et al., 2008; Woolf et al., 2009; Levitan, 2013) found that users' satisfaction about  
736 their interaction with an ECA is greater when the ECA adapts its behaviour to user's one. From these  
737 results, we could expect that the user would be more satisfied about the interaction when the ECA adapted  
738 its low-level signals according to their behaviours. We also assumed that the ECA adapting its lip corner  
739 puller (that is related to smiling) would be perceived as friendlier. Thus, our hypotheses were:

740 **H1Head**: when the ECA adapted its head rotation, the users would be *more satisfied* with the interaction  
741 compared to the users interacting with the ECA in the *Random* condition.

742 **H2aLips**: when the ECA adapted its lip corners movement (AU12), the users would be *more satisfied* with  
743 the interaction compared to the users interacting with the ECA in the *Random* condition.

744 **H2bLips**: when the ECA adapted its lip corners movement (AU12), it would be evaluated as *friendlier*  
745 compared to the ECA in the *Random* condition.

746 **H3Eyes**: when the ECA adapted its eyes rotation, the users would be *more satisfied* with the interaction  
747 compared to the users interacting with the ECA in the *Random* condition.

748 **H4aAll**: when the ECA adapted its head and eyes rotations and lip corners movement, the users would  
 749 be *more satisfied* with the interaction compared to the users interacting with the ECA in the *Random*  
 750 condition.

751 **H4bAll**: when the ECA adapts its head and eyes rotations and lip corners movement, it would be evaluated  
 752 as *friendlier* compared to the ECA in the *Random* condition.

### 753 9.3 Analysis and Results

754 101 participants (55 females), almost equally distributed among the 5 conditions, took part of our  
 755 experiment. 95% of participants were native French speakers. 32% of them were in the range 18-25 years  
 756 old, 17% were in the range 25-36, 21% in the range 36-45, 18% in the range of 46-55 and 12% were over  
 757 55 years old. For each dimension of the user's engagement questionnaire, as well as for that about the  
 758 perceived friendliness of the ECA, Cronbach's  $\alpha$ s were  $> 0.8$ ; we then computed the mean of the scores in  
 759 order to have one score for each dimension. Mean and standard deviation of each measured dimension for  
 760 each of the five conditions are showed in Table 4.

**Table 4.** Mean  $\pm$  standard deviation of each dimension of the questionnaires (each row of the table), for each of the five conditions (each column). \* indicates that the score is significantly different compared to the Random condition ( $p\text{-adj} < .05$ ).

	<i>Random</i>	<i>Head</i>	<i>Lip Corners</i>	<i>Eyes</i>	<i>All</i>
<i>Competence</i>	2.98 $\pm$ 1.22	3.45 $\pm$ 0.81	3.73 $\pm$ 0.73	3.65 $\pm$ 1.06	3.61 $\pm$ 1.12
<i>Distance</i>	2.5 $\pm$ 1.12	2.6 $\pm$ 1.03	1.76 $\pm$ 0.97	2 $\pm$ 1.12	1.47 $\pm$ 1.03
<i>Friendliness</i>	3.03 $\pm$ 1.12	3.22 $\pm$ 0.86	3.80 $\pm$ 0.83	3.33 $\pm$ 0.86	4.09 $\pm$ 0.90*
<i>Involvement</i>	2.65 $\pm$ 1.22	2.65 $\pm$ 1.15	3.52 $\pm$ 1.00*	2.83 $\pm$ 1.33	3.60 $\pm$ 1.07
<i>Realism</i>	1.7 $\pm$ 0.92	1.95 $\pm$ 0.82	2.52 $\pm$ 1.12	2.08 $\pm$ 0.90	1.73 $\pm$ 0.86
<i>Relevance</i>	2.95 $\pm$ 1.38	3.86 $\pm$ 0.72	3.97 $\pm$ 0.79*	3.5 $\pm$ 1.24	3.80 $\pm$ 1.01
<i>Satisfaction</i>	2.46 $\pm$ 1.21	2.84 $\pm$ 0.77	3.39 $\pm$ 0.06	3.27 $\pm$ 1.08	3.39 $\pm$ 0.93

761 As our data were not normally distributed (Shapiro test's  $p < 0.5$ ), we used unpaired Wilcoxon test  
 762 (equivalent to t-test) to measure how participants ratings differed between the *Random* condition and each  
 763 of the other conditions.

764 In *Head* condition, we could not find differences between the conditions. We conclude that the hypothesis  
 765 **H1Head** is rejected.

766 In the *Lip Corners* condition, compared to participants in the *Random* condition, participants in the *Lip*  
 767 *Corners* condition were more involved ( $W = 98.5$ ,  $p\text{-adj} < .05$ ). We can also note that the ECA was  
 768 evaluated as more positive on the *relevance* dimension ( $W = 104.5$ ,  $p\text{-adj} < .05$ ). We can conclude that  
 769 the hypotheses **H2aLips** and **H2bLips** are not validated, but the adaptation of lip corners movement still  
 770 has a positive effect on other dimensions related to user's engagement.

771 In the *Eyes* condition, participants were satisfied with the ECA as with the ECA in the *Random* condition.  
 772 Thus, the hypothesis **H3Eyes** is rejected.

773 In the *All* condition, the ECA was evaluated as friendlier ( $W = 104.5$ ,  $p\text{-adj} < .05$ ) than the ECA in the  
 774 *Random* condition. So, **H4aAll** is supported, while **H4bAll** is rejected.

775 Results of the *NARS* questionnaire indicated that 40%, respectively 30% and 30%, of participants  
776 had a positive, respectively neutral and negative, attitude toward virtual agents. An ANOVA test was  
777 performed to study the influence of participants' a-priori toward virtual agents on their engagement in  
778 the interaction. Participants' prior attitude toward ECAs had a main effect on participants' *distance*  
779 ( $F(1, 93) = 5.13, p < .05$ ). Results of pairwise comparisons with Bonferroni adjustment highlighted that  
780 participants with prior negative attitude were less engaged (more distant ( $p\text{-adj} < .05$ ) and less involved  
781 ( $p\text{-adj} < .05$ )) than those with prior positive attitude.

## 782 9.4 Discussion

783 The results of this study showed that participants engagement and perception of ECA's friendliness were  
784 positively impacted when the ECA adapted its low-level signals. These results were significant only when  
785 the ECA adapted its lip corners movement (AU12) to user's behaviour (mainly their smile), that is, in the  
786 *Lip Corners* and *All* conditions. In the case of head and eyes rotation adaptation, we found a trend on  
787 some dimensions but no significant differences compared to the *Random* condition. These results could be  
788 caused by the adopted evaluation setting where ECA and user faced each other. During the interaction,  
789 most participants gazed at the ECA without doing any postural shift or even changing their gaze and head  
790 direction. They were mainly still and staring at the ECA. The adaptive behaviours, i.e., head and eyes  
791 rotation of the ECA computed from user's behaviours, remained constant throughout the interaction. They  
792 reflected participants' behaviours (that were not moving much). Thus, in the *Head* and *Eyes* adapting  
793 conditions the ECA showed much less expressiveness and may have appeared much less lively, which may  
794 have impacted participants' engagement in the interaction.

## 10 GENERAL DISCUSSION

795 In our studies, we applied the Interaction Adaptation Theory (see Section 2) on the ECA. That is, our  
796 adapting ECA had the Requirement R that it needed to adapt in order to have a successful interaction.  
797 Its Desire D was to maximise user's experience by eliciting a specific impression towards the user, or  
798 maintaining user's engagement. Finally, its expectations E were that the user's experience would be better  
799 when interacting with an adaptive ECA. All these factors rely on the general hypothesis that the user  
800 expects to interact with a social entity. According to this hypothesis, the ECA should adapt its behaviour  
801 like humans do (Appel et al., 2012).

802 We have looked at different adaptation mechanisms through three studies, each focusing on a specific  
803 type of adaptation. In our studies we found these mechanisms impacted user's experience of the interaction  
804 and their perception of the ECA. Moreover, in all three studies, interacting with an adaptive ECA vs a  
805 non-adaptive ECA tended to be more positively perceived. More precisely, manipulating agent's behaviours  
806 (Study 1) had an impact on user's perception of the ECA while low-level adaptation (Study 3) positively  
807 influenced user's experience of the interaction. Regarding managing conversational strategies (Study 2),  
808 the ECA was perceived warmer when it managed those that increased user's engagement vs when it did  
809 not change them all along the interaction.

810 These results suggest that the IAT framework allows enhancing human-agent interaction. Indeed, the  
811 adaptive ECA shows some improvement in the quality of the interaction and the perception of the ECA in  
812 terms of social attitudes.

813 However, not all our hypotheses were verified. This could be related to the fact that we based our  
814 framework on the general hypothesis that the user expects to interact with a social entity. The ECA did not  
815 take into account the fact that also the user had their specific Requirements, Desires and Expectations, the  
816 expectancy to interact with a social agent. Yet, the ECA did not check if the user still considered it as a



817 social entity during the interaction. It based its behaviours only from human's detected engagement and  
818 impressions. Moreover, the modules to detect engagement or impressions work on a given time window,  
819 but they do not consider their evolution through time. For example, the engagement module computes that  
820 participants are engaged if they look straight at the ECA without reporting any information stating the  
821 participants stare fixedly at the ECA. The fact participants do not change their gaze direction toward the  
822 ECA could be interpreted as participants do not view the ECA as a social entity with human-like qualities  
823 (Appel et al., 2012).

824 **Expectancy violation theory (Burgoon, 1993) could help better understanding this gap. This theory**  
825 **explains how confirmations and violations of people's expectancies affect communication outcomes such**  
826 **as attraction, liking, credibility persuasion, and learning. In particular, positive violations are predicted to**  
827 **produce better outcomes than positive confirmations, and negative violations are predicted to produce worse**  
828 **outcomes than negative confirmations. Expectancy violation theory have already been demonstrated to**  
829 **affect human-human interaction (Burgoon, 1993), as well as when people are in front of an ECA (Burgoon**  
830 **et al., 2016; Biancardi et al., 2017b) or a robot (Weber et al., 2018). In our work we took into account**  
831 **the role of expectancies as part of IAT theory. Our results suggest that expectancies could play a more**  
832 **important role than the one we attributed to them, and that they should be better modelled when developing**  
833 **human-agent adaptation. Future works in this context should combine Expectancy Violation Theory with**  
834 **IAT. In this way, the ECA should be able to detect user's expectancies in terms of beliefs and desires. It**  
835 **should also be able to check if those expectancies about the interaction correspond to the expected ones,**  
836 **and then react accordingly. For example, in our studies we found some effects of people's a-priori about**  
837 **virtual agents: people who got higher scores in the NARS questionnaire generally perceived the ECA**  
838 **warmer, compared to people who got lower scores in the NARS questionnaire. This effect could have been**  
839 **mitigated if the agent could detect the user's a-priori.**

840 Even with these limits, the results of our studies show that an adaptive model for a virtual agent inspired  
841 from IAT theory partially managed to produce an impact on user's experience of the interaction and on  
842 their perception of the ECA. **This could be useful to personalise systems for different applications such as**  
843 **education, healthcare or entertainment, where there is a need of adaptation according to users' type and**  
844 **behaviours and/or interaction contexts.**

845 The different adaptation models we developed also confirm the potential of automatic behaviour analysis  
846 for the estimation of different user's characteristics. These methods can be used to better understand the  
847 user's profile and can also be applied to human-computer interaction in general to inform adaptation models  
848 in real-time.

849 Moreover, the use of adaptation mechanisms inspired from IAT theory could help mitigate the negative  
850 effect of some interactions problems more difficult to solve, due for example to technological limits of  
851 the system. Indeed, adaptation acts to enhance the agent's perception and the perceived interaction quality.  
852 Improving adaptation mechanisms may help to counterbalance technological shortenings. It may also  
853 improve the acceptability of innovative technologies that are likely to be part of our daily lives, in the  
854 context of work, health, leisure, etc.

## 11 CONCLUSION AND FUTURE WORK

855 In this paper we investigated adaptation in human-agent interaction. In particular, we reported our work  
856 about three models focusing on different levels of agent's adaptation (behavioural, conversational and signal  
857 level), by framing them in the same theoretical framework (Burgoon et al., 2007). In all the adaptation  
858 mechanisms implemented in the models, user's behaviour is taken into account by the ECA during the

859 interaction in real-time. Evaluation studies showed a tendency towards a positive impact of the adaptive  
860 ECA on user's experience and perception of the ECA, encouraging us to continue to investigate in this  
861 direction.

862 One limitation of our models is their reliance on the interaction scenario. Indeed, to obtain good  
863 performances of adaptation models using reinforcement learning algorithms, a scenario including an  
864 adequate number of steps is required. In our case, the agent ended up selecting a specific combination of  
865 behaviours only during the late part of the interaction. A longer interaction with more steps would allow  
866 an adaptive agent using reinforcement learning algorithms to better learn. Another possibility would be  
867 to have participants interacting more than once with the virtual agent. This latter would require adding a  
868 memory adaptation module (Ahmad et al., 2017). This would also allow for checking whether the same user  
869 prefers the same behaviour and/or conversational strategies of the agent over several interactions. Similarly,  
870 regarding adaptation models reflecting user's behaviour, the less the user moves during the interaction, the  
871 less the agent's expressivity level is. The interaction scenario should be designed in order to elicit user's  
872 participation, including strategies to tickle users when they become too still and non reactive. For example,  
873 one could use a scenario including a collaborative task where both agent and user would interact with  
874 different objects. In such a setting, though it would require to extend our engagement detection module to  
875 include joint attention, we expect the participants would also perform much more head movements that in  
876 turn could be useful for a better low-level adaptation of the agent.

877 In the future, our work could be improved and explored along further axes. We list three of them here.  
878 First, the three models presented in this paper were implemented and evaluated independently from each  
879 other. It could be interesting to merge the three adaptation mechanisms in a broader model and investigate  
880 the impacts of agent's adaptation along different levels at the same time. Second, in our studies, the agent  
881 adapted its behaviours to the user's ones without considering if the relationship between the behaviours of  
882 the dyad showed any specific interaction patterns. In particular, we have not made explicit if the agent's  
883 behaviour should either match, reciprocate, complement, compensate or mirror their human interlocutor's  
884 behaviour (Burgoon et al., 2007). Also, we have not measured any similarities, synchronisation or imitation  
885 between user's and agent's behaviour when we analysed the data of our studies. Since adaptation may  
886 be signalled through a larger variety of behaviour manifestations during an interaction, more adaptation  
887 mechanisms could be implemented. One last important direction for future work concerns the improvement  
888 of the interaction with the user. This would reduce possible secondary effects of uncontrolled variables,  
889 such as user's expectancies, and allow for better studying the effects of agent's adaptation. We aim to  
890 improve the agent's conversational skills, to ensure conversation repairs and interruptions and by letting  
891 the user choose the topic of conversation (e.g., from a set of possible ones) and drive the discussion. **In**  
892 **addition to these improvements, user's expectancies should also be better modelled by taking into account**  
893 **Expectancy Violation Theory in addition to Interaction Adaptation Theory.**

## REFERENCES

- 894 Ahmad, M. I., Mubin, O., and Orlando, J. (2017). Adaptive social robot for sustaining social engagement  
895 during long-term children–robot interaction. *International Journal of Human–Computer Interaction*,  
896 33(12):943–962.
- 897 Altman, I., Vinsel, A., and Brown, B. B. (1981). Dialectic conceptions in social psychology: An application  
898 to social penetration and privacy regulation. In *Advances in experimental social psychology*, volume 14,  
899 pages 107–160. Elsevier.

- 900 Andersen, P. A. (1985). Nonverbal immediacy in interpersonal communication. In Siegman, A. A. and  
901 Feldstein, S., editors, *Multichannel integrations of nonverbal behavior*, pages 1–36. Psychology Press.
- 902 Appel, J., von der Pütten, A., Krämer, N. C., and Gratch, J. (2012). Does humanity matter? analyzing  
903 the importance of social cues and perceived agency of a computer system for the emergence of social  
904 reactions during human-computer interaction. *Advances in Human-Computer Interaction*, 2012.
- 905 Aragonés, J. I., Poggio, L., Sevillano, V., Pérez-López, R., and Sánchez-Bernardos, M.-L. (2015).  
906 Measuring warmth and competence at inter-group, interpersonal and individual levels/medición de  
907 la cordialidad y la competencia en los niveles intergrupales, interindividual e individual. *Revista de*  
908 *Psicología Social*, 30(3):407–438.
- 909 Argyle, M. (1972). *Non-verbal communication in human social interaction*. Cambridge University Press.
- 910 Argyle, M. and Dean, J. (1965). Eye-contact, distance and affiliation. *Sociometry*, 28(3):289–304.
- 911 Bailenson, J. and Yee, N. (2005). Digital chameleons: Automatic assimilation of nonverbal gestures in  
912 immersive virtual environments. *Psychological Science*, 16:814–819.
- 913 Baltrušaitis, T., Robinson, P., and Morency, L.-P. (2016). Openface: an open source facial behavior analysis  
914 toolkit. In *Applications of Computer Vision (WACV), 2016 IEEE Winter Conference on*, pages 1–10.  
915 IEEE.
- 916 Bergmann, K., Eyssel, F., and Kopp, S. (2012). A second chance to make a first impression? how  
917 appearance and nonverbal behavior affect perceived warmth and competence of virtual agents over time.  
918 In *International Conference on Intelligent Virtual Agents*, pages 126–138. Springer.
- 919 Bernieri, F. J., Reznick, J. S., and Rosenthal, R. (1988). Synchrony, pseudosynchrony, and dissynchrony:  
920 measuring the entrainment process in mother-infant interactions. *Journal of personality and social*  
921 *psychology*, 54(2):243.
- 922 Bevacqua, E., Mancini, M., and Pelachaud, C. (2008). A listening agent exhibiting variable behaviour. In  
923 *International Conference on Intelligent Virtual Agents*, pages 262–269. Springer.
- 924 Biancardi, B., Cafaro, A., and Pelachaud, C. (2017a). Analyzing first impressions of warmth and  
925 competence from observable nonverbal cues in expert-novice interactions. In *Proceedings of the 19th*  
926 *ACM International Conference on Multimodal Interaction*, pages 341–349.
- 927 Biancardi, B., Cafaro, A., and Pelachaud, C. (2017b). Could a virtual agent be warm and competent?  
928 investigating user’s impressions of agent’s non-verbal behaviours. In *Proceedings of the 1st ACM*  
929 *SIGCHI International Workshop on Investigating Social Interactions with Artificial Agents*, pages 22–24.
- 930 Biancardi, B., Mancini, M., Lerner, P., and Pelachaud, C. (2019a). Managing an agent’s self-presentational  
931 strategies during an interaction. *Frontiers in Robotics and AI*, 6:93.
- 932 Biancardi, B., Wang, C., Mancini, M., Cafaro, A., Chanel, G., and Pelachaud, C. (2019b). A computational  
933 model for managing impressions of an embodied conversational agent in real-time. In *2019 International*  
934 *Conference on Affective Computing and Intelligent Interaction (ACII)*.
- 935 Bickmore, T., Pfeifer, L., and Schulman, D. (2011). Relational agents improve engagement and learning  
936 in science museum visitors. In *International Conference on Intelligent Virtual Agents*, pages 55–67.  
937 Springer.
- 938 Bickmore, T. W., Vardoulakis, L. M. P., and Schulman, D. (2013). Tinker: a relational agent museum guide.  
939 *Autonomous agents and multi-agent systems*, 27(2):254–276.
- 940 Burgoon, J. K. (1993). Interpersonal expectations, expectancy violations, and emotional communication.  
941 *Journal of Language and Social Psychology*, 12(1-2):30–48.
- 942 Burgoon, J. K., Bonito, J. A., Lowry, P. B., Humpherys, S. L., Moody, G. D., Gaskin, J. E., and Giboney,  
943 J. S. (2016). Application of expectancy violations theory to communication with and judgments about  
944 embodied agents during a decision-making task. *International Journal of Human-Computer Studies*,

- 945 91:24–36.
- 946 Burgoon, J. K., Stern, L. A., and Dillman, L. (2007). *Interpersonal adaptation: Dyadic interaction patterns*.  
947 Cambridge University Press.
- 948 Cafaro, A., Vilhjálmsón, H. H., and Bickmore, T. (2016). First impressions in human–agent virtual  
949 encounters. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 23(4):1–40.
- 950 Cafaro, A., Wagner, J., Baur, T., Dermouche, S., Torres Torres, M., Pelachaud, C., André, E., and Valstar,  
951 M. (2017). The NoXi database: multimodal recordings of mediated novice-expert interactions. In  
952 *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, pages 350–359.  
953 ACM.
- 954 Callejas, Z., Ravenet, B., Ochs, M., and Pelachaud, C. (2014). A computational model of social attitudes  
955 for a virtual recruiter. In *Proceedings of the 13th international conference on Autonomous Agents and*  
956 *Multi-Agent Systems*, pages 93–100.
- 957 Camurri, A., Coletta, P., Massari, A., Mazzarino, B., Peri, M., Ricchetti, M., Ricci, A., and Volpe, G. (2004).  
958 Toward real-time multimodal processing: Eyesweb 4.0. In *Proceedings of the Artificial Intelligence and*  
959 *the Simulation of Behaviour (AISB), 2004 convention: motion. Emotion and cognition*, pages 22–26.
- 960 Cappella, J. N. (1981). Mutual influence in expressive behavior: Adult–adult and infant–adult dyadic  
961 interaction. *Psychological bulletin*, 89(1):101–132.
- 962 Cappella, J. N. (1991). Mutual adaptation and relativity of measurement. *Studying interpersonal interaction*,  
963 1:103–117.
- 964 Cappella, J. N. and Greene, J. O. (1982). A discrepancy-arousal explanation of mutual influence in  
965 expressive behavior for adult and infant-adult interaction. *Communications Monographs*, 49(2):89–114.
- 966 Cassell, J., Bickmore, T., Vilhjálmsón, H., and Yan, H. (2000). More Than Just a Pretty Face: Affordances  
967 of Embodiment. In *International Conference of Intelligent Virtual Agents*, pages 52–59. Springer.
- 968 Castellano, G., Pereira, A., Leite, I., Paiva, A., and McOwan, P. W. (2009). Detecting user engagement  
969 with a robot companion using task and social interaction-based features. In *Proceedings of the 2009*  
970 *international conference on Multimodal interfaces*, pages 119–126. ACM.
- 971 Chartrand, T. L. and Bargh, J. A. (1999). The chameleon effect: the perception–behavior link and social  
972 interaction. *Journal of personality and social psychology*, 76(6):893–910.
- 973 Condon, W. S. and Ogston, W. D. (1971). Speech and body motion synchrony of the speaker-hearer. In  
974 Horton, D. L. and J, J. J., editors, *The perception of Language*, pages 150–184. Columbus, Ohio: Charles  
975 Merrill.
- 976 Coninx, A., Baxter, P., Oleari, E., Bellini, S., Bierman, B., Henkemans, O. B., Cañamero, L., Cosi, P.,  
977 Enescu, V., Espinoza, R. R., et al. (2016). Towards long-term social child-robot interaction: using  
978 multi-activity switching to engage young users. *Journal of Human-Robot Interaction*, 5(1):32–67.
- 979 Corrigan, L. J., Peters, C., Küster, D., and Castellano, G. (2016). Engagement perception and generation  
980 for social robots and virtual agents. In Esposito, A. and Jain, L. C., editors, *Toward Robotic Socially*  
981 *Believable Behaving Systems*, volume 1, pages 29–51. Springer.
- 982 Cuddy, A. J., Fiske, S. T., and Glick, P. (2008). Warmth and competence as universal dimensions of social  
983 perception: The stereotype content model and the bias map. *Advances in experimental social psychology*,  
984 40:61–149.
- 985 Dermouche, S. and Pelachaud, C. (2019). Engagement modeling in dyadic interaction. In *2019*  
986 *International Conference on Multimodal Interaction*, pages 440–445.
- 987 Dindia, K. (1988). A comparison of several statistical tests of reciprocity of self-disclosure. *Communication*  
988 *Research*, 15(6):726–752.

- 989 Duchenne, B. (1990). The mechanism of human facial expression or an electro-physiological analysis of  
990 the expression of the emotions (a. cuthbertson, trans.). *New York: Cambridge University Press.(Original*  
991 *work published 1862).*
- 992 Ekman, P., Friesen, W., and Hager, J. (2002). *Facial action coding system (FACS). A human face.* Research  
993 Nexus, Salt Lake City.
- 994 Fischer-Lokou, J., Martin, A., Guéguen, N., and Lamy, L. (2011). Mimicry and propagation of prosocial  
995 behavior in a natural setting. *Psychological reports*, 108(2):599–605.
- 996 Fiske, S. T., Cuddy, A. J., and Glick, P. (2007). Universal dimensions of social cognition: Warmth and  
997 competence. *Trends in cognitive sciences*, 11(2):77–83.
- 998 Gallois, C., Ogay, T., and Giles, H. (2005). Communication accommodation theory: A look back and a  
999 look ahead. In Gudykunst, W. B., editor, *Theorizing about intercultural communication*, pages 121–148.  
1000 SAGE.
- 1001 Giles, H., Coupland, N., and Coupland, J. (1991). Accommodation theory: Communication, context, and  
1002 consequence. In Giles, H, C. J. and Coupland, N., editors, *Studies in emotion and social interaction.*  
1003 *Contexts of accommodation: Developments in applied sociolinguistics*, volume 1, pages 1–68. Cambridge  
1004 University Press.
- 1005 Gordon, G., Spaulding, S., Westlund, J. K., Lee, J. J., Plummer, L., Martinez, M., Das, M., and Breazeal,  
1006 C. (2016). Affective personalization of a social robot tutor for children’s second language skills. In  
1007 *Thirtieth AAAI Conference on Artificial Intelligence*, page 3951–3957.
- 1008 Gouldner, A. W. (1960). The norm of reciprocity: A preliminary statement. *American sociological review*,  
1009 25(2):161–178.
- 1010 Gueguen, N., Jacob, C., and Martin, A. (2009). Mimicry in social interaction: Its effect on human judgment  
1011 and behavior. *European Journal of Social Sciences*, 8(2):253–259.
- 1012 Hale, J. L. and Burgoon, J. K. (1984). Models of reactions to changes in nonverbal immediacy. *Journal of*  
1013 *Nonverbal Behavior*, 8(4):287–314.
- 1014 Hemminahaus, J. and Kopp, S. (2017). Towards adaptive social behavior generation for assistive robots  
1015 using reinforcement learning. In *2017 12th ACM/IEEE International Conference on Human-Robot*  
1016 *Interaction (HRI)*, pages 332–340. IEEE.
- 1017 Huang, L., Morency, L.-P., and Gratch, J. (2010). Learning backchannel prediction model from parasocial  
1018 consensus sampling: a subjective evaluation. In *International Conference on Intelligent Virtual Agents*,  
1019 pages 159–172. Springer.
- 1020 Huang, L., Morency, L.-P., and Gratch, J. (2011). Virtual rapport 2.0. In *International Conference on*  
1021 *Intelligent Virtual Agents*, pages 68–79. Springer.
- 1022 Infante, D. A., Rancer, A. S., and Avtgis, T. A. (2010). *Contemporary communication theory.* Kendall  
1023 Hunt Dubuque, IA.
- 1024 Jones, E. E. and Pittman, T. S. (1982). Toward a general theory of strategic self-presentation. *Psychological*  
1025 *perspectives on the self*, 1(1):231–262.
- 1026 Judd, C. M., James-Hawkins, L., Yzerbyt, V., and Kashima, Y. (2005). Fundamental dimensions of  
1027 social judgment: understanding the relations between judgments of competence and warmth. *Journal of*  
1028 *personality and social psychology*, 89(6):899–913.
- 1029 Katehakis, M. N. and Veinott Jr, A. F. (1987). The multi-armed bandit problem: decomposition and  
1030 computation. *Mathematics of Operations Research*, 12(2):262–268.
- 1031 Kopp, S., Gesellensetter, L., Krämer, N. C., and Wachsmuth, I. (2005). A conversational agent as museum  
1032 guide—design and evaluation of a real-world application. In *International Conference on Intelligent*  
1033 *Virtual Agents*, pages 329–343. Springer.

- 1034 Lafferty, J. D., McCallum, A., and Pereira, F. C. N. (2001). Conditional random fields: Probabilistic models  
1035 for segmenting and labeling sequence data. In *Proceedings of the Eighteenth International Conference on*  
1036 *Machine Learning, ICML '01*, pages 282–289, San Francisco, CA, USA. Morgan Kaufmann Publishers  
1037 Inc.
- 1038 Lakin, J. L. and Chartrand, T. L. (2003). Using nonconscious behavioral mimicry to create affiliation and  
1039 rapport. *Psychological science*, 14(4):334–339.
- 1040 Levitan, R. (2013). Entrainment in spoken dialogue systems: Adopting, predicting and influencing user  
1041 behavior. In *Proceedings of the 2013 NAACL HLT Student Research Workshop*, pages 84–90.
- 1042 Lisetti, C., Amini, R., Yasavur, U., and Rishe, N. (2013). I can help you change! an empathic virtual agent  
1043 delivers behavior change health interventions. *ACM Transactions on Management Information Systems*  
1044 (*TMIS*), 4(4):1–28.
- 1045 Liu, C., Conn, K., Sarkar, N., and Stone, W. (2008). Online affect detection and robot behavior adaptation  
1046 for intervention of children with autism. *IEEE transactions on robotics*, 24(4):883–896.
- 1047 Lubold, N., Walker, E., and Pon-Barry, H. (2016). Effects of voice-adaptation and social dialogue on  
1048 perceptions of a robotic learning companion. In *2016 11th ACM/IEEE International Conference on*  
1049 *Human-Robot Interaction (HRI)*, pages 255–262. IEEE.
- 1050 Maricchiolo, F., Gnisci, A., Bonaiuto, M., and Ficca, G. (2009). Effects of different types of hand gestures  
1051 in persuasive speech on receivers' evaluations. *Language and Cognitive Processes*, 24(2):239–266.
- 1052 Mills, C., Bosch, N., Krasich, K., and D'Mello, S. K. (2019). Reducing mind-wandering during vicarious  
1053 learning from an intelligent tutoring system. In *International Conference on Artificial Intelligence in*  
1054 *Education*, pages 296–307. Springer.
- 1055 Nomura, T., Kanda, T., and Suzuki, T. (2006). Experimental investigation into influence of negative  
1056 attitudes toward robots on human–robot interaction. *AI & Society*, 20(2):138–150.
- 1057 Paiva, A., Leite, I., Boukricha, H., and Wachsmuth, I. (2017). Empathy in virtual agents and robots: A  
1058 survey. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 7(3):1–40.
- 1059 Pecune, F., Cafaro, A., Chollet, M., Philippe, P., and Pelachaud, C. (2014). Suggestions for Extending  
1060 SAIBA with the VIB Platform. In *Workshop on Architectures and Standards for IVAs, held at the '14th*  
1061 *International Conference on Intelligent Virtual Agents (IVA 2014)*, pages 16–20, Boston, MA, USA.  
1062 Bielefeld eCollections.
- 1063 Peeters, G. and Czapinski, J. (1990). Positive-negative asymmetry in evaluations: The distinction between  
1064 affective and informational negativity effects. *European review of social psychology*, 1(1):33–60.
- 1065 Pelachaud, C. (2009). Modelling multimodal expression of emotion in a virtual agent. *Philosophical*  
1066 *Transactions of the Royal Society B: Biological Sciences*, 364(1535):3539–3548.
- 1067 Pennebaker, J. W. (2011). The secret life of pronouns. *New Scientist*, 211(2828):42–45.
- 1068 Raffard, s., Salesse, R., Bortolon, C., Bardy, B., Henriques, J., Ludovic, M., Stricker, D., and Capdevielle,  
1069 D. (2018). Using mimicry of body movements by a virtual agent to increase synchronization behavior  
1070 and rapport in individuals with schizophrenia. *Scientific Reports*, 8:1–10.
- 1071 Ritschel, H., Baur, T., and André, E. (2017). Adapting a robot's linguistic style based on socially-aware  
1072 reinforcement learning. In *Robot and Human Interactive Communication (RO-MAN), 2017 26th IEEE*  
1073 *International Symposium on*, pages 378–384. IEEE.
- 1074 Rizzo, A., Shilling, R., Forbell, E., Scherer, S., Gratch, J., and Morency, L.-P. (2016). Autonomous virtual  
1075 human agents for healthcare information support and clinical interviewing. In *Artificial intelligence in*  
1076 *behavioral and mental health care*, pages 53–79. Elsevier.
- 1077 Rosenberg, S., Nelson, C., and Vivekananthan, P. (1968). A multidimensional approach to the structure of  
1078 personality impressions. *Journal of personality and social psychology*, 9(4):283.

- 1079 Schröder, M., Bevacqua, E., Cowie, R., Eyben, F., Gunes, H., Heylen, D., ter Maat, M., McKeown, G.,  
1080 Pammi, S., Pantic, M., Pelachaud, C., Schuller, B. W., de Sevin, E., Valstar, M. F., and Wöllmer, M.  
1081 (2015). Building autonomous sensitive artificial listeners. In *2015 International Conference on Affective*  
1082 *Computing and Intelligent Interaction (ACII)*, pages 456–462.
- 1083 Sidner, C. L., Bickmore, T., Nooraie, B., Rich, C., Ring, L., Shayganfar, M., and Vardoulakis, L. (2018).  
1084 Creating new technologies for companionable agents to support isolated older adults. *ACM Transactions*  
1085 *on Interactive Intelligent Systems (TiiS)*, 8(3):1–27.
- 1086 Swartout, W., Traum, D., Artstein, R., Noren, D., Debevec, P., Bronnenkant, K., Williams, J., Leuski, A.,  
1087 Narayanan, S., Piepol, D., et al. (2010). Ada and grace: Toward realistic and engaging virtual museum  
1088 guides. In *International Conference on Intelligent Virtual Agents*, pages 286–300. Springer.
- 1089 Toma, C. L. (2014). Towards conceptual convergence: An examination of interpersonal adaptation.  
1090 *Communication Quarterly*, 62(2):155–178.
- 1091 van Vugt, H. C., Hoorn, J. F., Konijn, E. A., and de Bie Dimitriadou, A. (2006). Affective affordances:  
1092 Improving interface character engagement through interaction. *International Journal of Human*  
1093 *Computer Studies*, 64(9):874–888.
- 1094 van Waterschoot, J., Bruijnes, M., Flokstra, J., Reidsma, D., Davison, D., Theune, M., and Heylen, D.  
1095 (2018). Flipper 2.0. In *International Conference on Intelligent Virtual Agents*, number November, pages  
1096 43–50. Springer.
- 1097 Verberne, F., Ham, J., Ponnada, A., and Midden, C. (2013). Trusting digital chameleons: The effect of  
1098 mimicry by a virtual social agent on user trust. In *International Conference on Persuasive Technology*,  
1099 pages 234–245.
- 1100 Wang, C., Biancardi, B., Mancini, M., Cafaro, A., Pelachaud, C., Pun, T., and Chanel, G. (2019). Impression  
1101 detection and management using an embodied conversational agent. In *International Conference on*  
1102 *Human-Computer Interaction*, pages 392–403. Springer.
- 1103 Weber, K., Ritschel, H., Aslan, I., Lingensfelder, F., and André, E. (2018). How to shape the humor of  
1104 a robot-social behavior adaptation based on reinforcement learning. In *Proceedings of the 20th ACM*  
1105 *International Conference on Multimodal Interaction*, pages 154–162.
- 1106 Wiering, M. A. (2005). Qv ( $\lambda$ )-learning: A new on-policy reinforcement learning algorithm. In  
1107 *Proceedings of the 7th european workshop on reinforcement learning*, pages 17–18.
- 1108 Wiggins, J. S. (1979). A psychological taxonomy of trait-descriptive terms: The interpersonal domain.  
1109 *Journal of Personality and Social Psychology*, 37(37):395–412.
- 1110 Wojciszke, B. and Abele, A. E. (2008). The primacy of communion over agency and its reversals in  
1111 evaluations. *European Journal of Social Psychology*, 38(7):1139–1147.
- 1112 Woolf, B., Bursleson, W., Arroyo, I., Dragon, T., Cooper, D., and Picard, R. (2009). Affect-aware  
1113 tutors: recognising and responding to student affect. *International Journal of Learning Technology*,  
1114 4(3-4):129–164.
- 1115 Yzerbyt, V., Provost, V., and Corneille, O. (2005). Not competent but warm... really? compensatory  
1116 stereotypes in the french-speaking world. *Group Processes & Intergroup Relations*, 8(3):291–308.
- 1117 Zhang, Z., Bickmore, T. W., and Paasche-Orlow, M. K. (2017). Perceived organizational affiliation and  
1118 its effects on patient trust: Role modeling with embodied conversational agents. *Patient education and*  
1119 *counseling*, 100(9):1730–1737.
- 1120 Zhao, R., Sinha, T., Black, A. W., and Cassell, J. (2016). Socially-aware virtual agents: Automatically  
1121 assessing dyadic rapport from temporal patterns of behavior. In *International Conference on Intelligent*  
1122 *Virtual Agents*, pages 218–233. Springer.