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# Heart Rate Monitoring as an Easy Way to Increase Engagement in Human-Agent Interaction

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**Abstract:** Physiological sensors are gaining the attention of manufacturers and users. As denoted by devices such as smartwatches or the newly released Kinect 2 – which can covertly measure heartbeats – or by the popularity of smartphone apps that track heart rate during fitness activities. Soon, physiological monitoring could become widely accessible and transparent to users. We demonstrate how one could take advantage of this situation to increase users’ engagement and enhance user experience in human-agent interaction. We created an experimental protocol involving embodied agents – “virtual avatars”. Those agents were displayed alongside a beating heart. We compared a condition in which this feedback was simply duplicating the heart rates of users to another condition in which it was set to an average heart rate. Results suggest a superior social presence of agents when they display feedback similar to users’ internal state. This physiological “similarity-attraction” effect may lead, with little effort, to a better acceptance of agents and robots by the general public.

## 1 INTRODUCTION

Covert sensing of users’ physiological state is likely to open new communication channels between human and computers. When anthropomorphic characteristics are involved – as with embodied agents – mirroring such physiological cues could guide users’ preferences in a cheap yet effective manner.

One aspect of human-computer interaction (HCI), albeit difficult to account for, lies in users’ engagement. Engagement may be seen as a way to increase performance, as in the definition given by (Matthews et al., 2002) for task engagement: an “effortful striving towards task goals”. In a broader acceptance, the notion of engagement is also related to fun and accounts for the overall user experience (Mandryk et al., 2006). Several HCI components can be tuned to improve engagement. For example, content and challenge need to be adapted and renewed to avoid boredom and maintain users in a state of flow (Berta et al., 2013). It is also possible to study interfaces: (Karlesky and Isbister, 2014) use tangible interactions in surrounding space to spur engagement and creativity. When the interaction encompasses embodied agents – either physically (i.e., robots) or not (on-screen

avatars) – then anthropomorphic characteristics can be involved to seek better human-agent connections.

Following the affective computing outbreak (Picard, 1995), studies using agents that possess human features in order to respond to users with the appropriate emotions and behaviors began to emerge. (Prendinger et al., 2004) created an “empathic” agent that serves as a companion during a job interview. While playing on empathy to engage users more deeply into the simulation was conclusive, the difficulty lies in the accurate recognition of emotions. Even using physiological sensors, as did the authors with galvanic skin response and electromyography, no signal processing could yet reach an accuracy of 100%, even on a reduced set of emotions – see (Lisetti and Nasoz, 2004) for a review.

Humans are difficult to comprehend for computers and, still, humans are more attracted to others – human or *machine* – that match their personalities (Lee and Nass, 2003). This finding is called “similarity-attraction” in (Lee and Nass, 2003) and was tested by the authors by matching the parameters of a synthesized speech (e.g., paralinguistic cues) to users, whenever they were introverted or extroverted. An analogous effect on social presence and engagement in HCI

has been described as well in (Reidsma et al., 2010), this time under the name of “synchrony” and focusing on nonverbal cues (e.g., gestures, choice of vocabulary, timing, ...). Unfortunately, being somewhat linked to a theory of mind, such improvements lean against tedious measures, for instance psychological tests or recordings of users’ behaviors. What if the similarity-attraction could be effective with cues that are much simpler and easier to set up?

Indeed, at a lower level of information, (Slovák et al., 2012) studied how the display of heart rate (HR) could impact social presence during human-human interaction. They showed that, without any further processing than the computation of an average heart-beat, users did report in various contexts being closer or more connected to the person with whom they shared their HR. We wondered if a similar effect could be obtained between a human and a machine. Moreover, we anticipated the rise of devices that could covertly measure physiological signals, such as the Kinect 2, which can use its cameras (color and infrared) to compute users’ HRs – the use of video feeds to perform volumetric measurements of organs is dubbed as “photoplethysmography” (Kranjec et al., 2014).

Consequently, we extended on the theory and we **hypothesized that users would feel more connected toward an embodied agent if it displays a heart rate similar to theirs, even if users do not realize that their own heart rates are being monitored.**

By relying on a simple mirroring of users’ physiology, we elude the need to test users’ personality (Lee and Nass, 2003) or to process – and eventually fail to recognize – their internal state (Prendinger et al., 2004). Creating agents too much alike humans may provoke rejection and deter engagement due to the uncanny valley effect (MacDorman, 2005). Since we do not emphasize the link between users’ physiological cues and the feedback given by agents, we hope to prevent such negative effect. The similarity-attraction applied to physiological data should work at an almost subconscious level. Furthermore, implicit feedback makes it easier to improve an existing HCI. As a matter of fact, only the feedback associated with the agent has to be added to the application; feedback that can then take a less anthropocentric form – e.g., see (Harrison et al., 2012) for the multiple meanings a blinking light can convey and (Huppi et al., 2003) for a use case with breathing-like features. Ultimately, our hypothesis proved robust, it could benefit to virtually any human-agent interaction, augmenting agent’s social presence, engaging users.

The following sections describe an experimental setup involving embodied agents that compares

two within-subject conditions: one condition during which agents display heartbeats replicating the HR of the users, and a second condition during which the displayed heartbeats are not linked to users. Our main contribution is to show first evidence that displaying identical heart rates makes users more engaged toward agents.

## 2 EXPERIMENT

The main task of our HCI consisted in listening to embodied agents while they were speaking aloud sentences extracted from a text corpus, as inspired by (Lee and Nass, 2003). When an agent was on-screen, a beating heart was displayed below it and an audio recording of a heart pulse was played along each (fake) beat. This feedback constituted our first within-subject factor: either the displayed HR was identical to the one of the subject (“human” condition), either it was set at an average HR (“medium” condition). The HR in the “medium” condition was ranging from 66 to 74 BPM (beats per minute), which is the grand average for our studied population (Agelink et al., 2001).

Agents possessed some random parameters: their gender (male or female), their appearance (6 faces of different ethnic groups for each gender), their voice (2 voices for each gender) and the voice pitch. Those various parameters aimed at concealing the true independent variable. Had we chosen a unique appearance for all the agents, subjects could have sought what was differentiating them. By individualizing agents we prevented subjects to discover that ultimately we manipulated the HR feedback. To make agents look more alive, their eyes were sporadically blinking and their mouths were animated while the text-to-speech system was playing.

In order to elicit bodily reactions, we chose sentences for which a particular valence has been associated with, and, as such, that could span a wide range of emotions. Valence relates to the hedonic tone and varies from negative (e.g., sad) to positive (e.g., happy) emotions (Picard, 1995). HR has a tendency to increase when one is experiencing extreme pleasantness, and to decrease when experiencing unpleasantness (Winton et al., 1984).

Our experiment was split in two parts (second within-subject factor). During the first session, called “disruptive” session (see Figure 1), subjects had to rate each sentence they heard on a 7-point Likert scale according to valence they perceived (very unpleasant to very pleasant). Sentences came from newspapers. A valence (negative, neutral or positive) was ran-

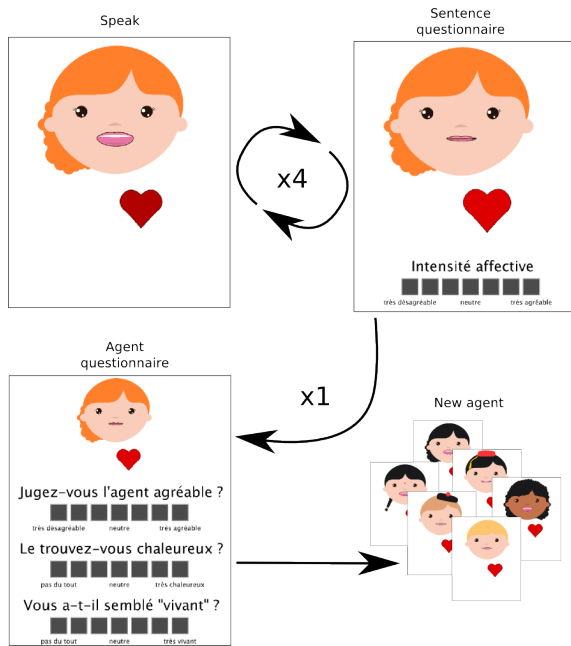


Figure 1: Procedure during the “disruptive” session: subjects rate the valence of each one of the sentences spoken by an agent. After 4 sentences, they rate agent’s social presence (3 items). Then a new agent appears. 20 agents, average time per agent  $\approx 62.2s$ .

domly chosen every 2 sentences. Every 4 sentences, subjects had to rate the social presence of the agent. Then a new randomly generated agent appeared, for a total of 20 agents, 10 for each “human”/“medium” condition.

As opposed to the first part, during the second part of the experiment, called “involving” session, sentences order was sequential (see Figure 2). Agents were in turns narrating a fairy tale. Subjects did not have to rate each sentence’s valence, instead they only rated the social presence of the agents. To match the length of the story, agents were shuffled every 6 sentences and there were 23 agents in total, 12 for the “human” condition, 11 for the “medium” condition.

Because of its distracting task and the nature of its sentences, the first part was more likely to disrupt human-agent connection; while the second part was more likely to involve subjects. This let us test the influence of the relation between users and agents on the perception of HR feedback. We chose not to randomize sessions order because we estimated that putting the “disruptive” session last would have made the overall experiment too fatiguing for subjects. A higher level of vigilance was necessary to sustain its distracting task and series of unrelated sentences. Subjects’ cognitive resources were probably higher at the beginning of the experiment.

We created a 2 (HR feedback: “human” vs “medium” condition)  $\times$  2 (nature of the task: “disruptive” vs “involving” session) within-subject experimental plan. Hence our two hypothesis. **H1**: Hear rate feedback replicating users’ physiology increases the social presence of agents. **H2**: This effect is more pronounced during an interaction involving more deeply agents.

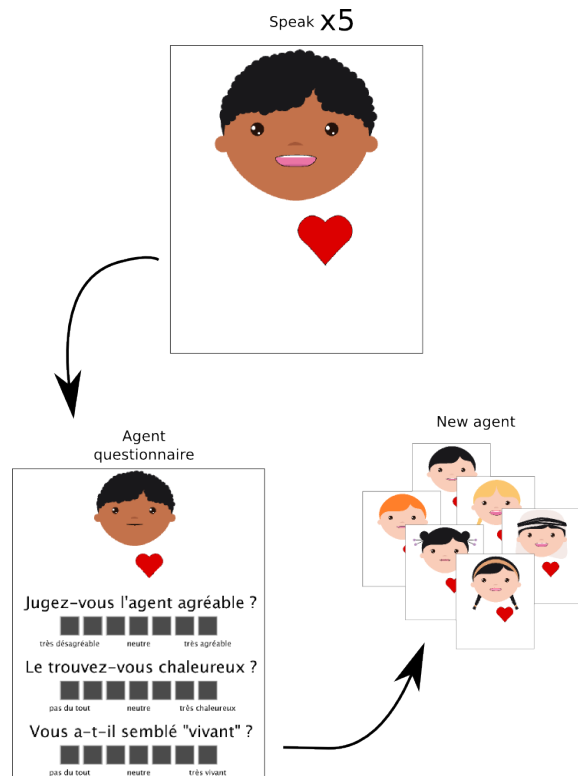


Figure 2: Procedure during the “involving” session: subjects rate agent’s social presence after it recited all its sentences. Then a new agent appears, continuing the tale. 23 agents, average time per agent  $\approx 46.6s$ .

## 2.1 Technical description

Most of the elements we describe in this section, hardware or software, come from open source movements, for which we are grateful. Authors would also like to thank the artist who made freely available the graphics on which agents are based<sup>1</sup>. All code and materials related to the study are freely available at [https://github.com/jfrey-phd/2015\\_physics\\_HR\\_code/](https://github.com/jfrey-phd/2015_physics_HR_code/).

### 2.1.1 Hardware

We chose to use a BVP (blood volume pulse) sensor to measure HR, employing the open hardware

<sup>1</sup><http://harridan.deviantart.com/>

Pulse Sensor<sup>2</sup> (see Figure 3 for a closeup). It assesses blood flow variations by emitting a light onto the skin and measuring back how fluctuates the intensity of the reflected light thanks to an ambient light photo sensor. Each heartbeat produces a characteristic signal. This technology is cheap and easy to implement. While it is less accurate than electrocardiography (ECG) recordings, we found the HR measures to be reliable enough for our purpose. Compared to ECG, BVP sensors are less intrusive and quicker to install – i.e., one sensor around a finger or on an earlobe instead of 2 or 3 electrodes on the chest. In addition, as far as general knowledge is concerned, BVP sensors are less likely to point out the exact nature of their measures. This “fuzziness” is important for our experimental protocol, as we want to be as close as possible to the real-life scenarios we foresee with devices such as the Kinect 2, where HR recordings will be transparent to users.

The BVP sensor was connected to an Arduino Due<sup>3</sup> (see Figure 3). Arduino boards have become a well-established platform for electrical engineering. The Due model comes forward due to its 12 bits resolution for operating analog sensors. The program uploaded into the Arduino Due was feeding the serial port with BVP values every 2ms, thus achieving a 500Hz sampling rate.

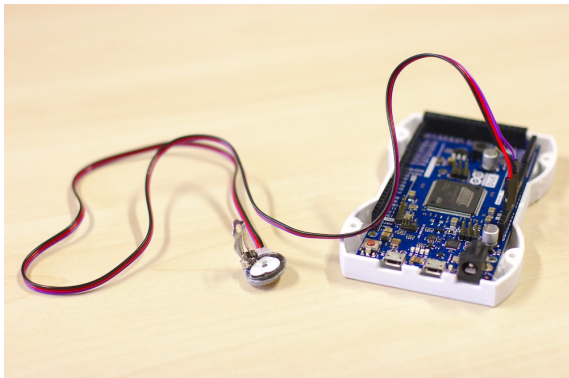


Figure 3: BVP (blood volume pulse) sensor measuring heartbeats, connected to an Arduino Due.

Two computers were used. One, a 14 inches screen laptop, was dedicated to the subject and ran the human-agent interaction. This computer was also plugged to the Arduino board to accommodate sensor’s cable length. A second laptop was used by the experimenter to monitor the experiment and to detect heartbeats. Computers were connected through an ethernet cable (network latency was inferior to 1ms).

<sup>2</sup><http://pulsesensor.myshopify.com>

<sup>3</sup><http://arduino.cc/>

## 2.1.2 Software and signal processing

Computers were running Kubuntu 13.10 operating system. The software on the client side was programmed with Processing framework<sup>4</sup>, version 2.2.1. Data acquired from the BVP sensor was streamed to the local network with ser2sock<sup>5</sup>. This serial port-to-TCP bridge software allowed us to reliably process and record data on our second computer. OpenViBE (Renard et al., 2010) version 0.18 was running on the experimenter’s computer to process BVP.

Within OpenViBE the BVP values were interpolated from 500 to 512Hz to ease computations. The script which received values from TCP was downsampling or oversampling packets’ content to ensure synchronization and decrease the risk of distorted signals due to network or computing latency. A 3Hz low-pass filter was applied to the acquired data in order to eliminate artifacts. Then a derivative was computed. Since a heartbeat provokes a sudden variation of blood flow, a pulsation was detected when the signal exceeded a certain threshold. This threshold was set during installation: values too low could produce false positives due to remaining noise, and values too high could skip heartbeats. Eventually a message was sent. See figure 4 for an overview of the signal processing.

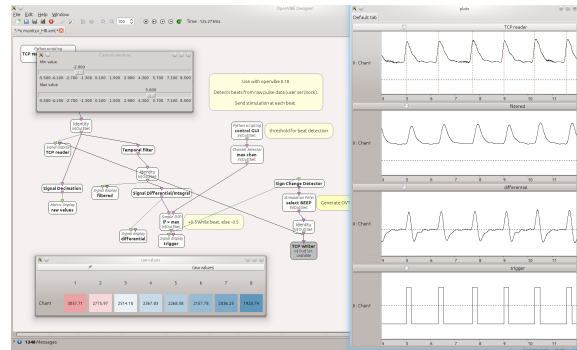


Figure 4: Signal processing of the BVP sensor with OpenViBE. A low-pass filtered and a first-derivative are used to detect heartbeats.

Once the main program received a pulse message, it computed the HR from the delay between two beats. This value was passed over the engine handling the HR feedback during the “human” condition. We purposely created an indirection here – using BPM values in separate handlers instead of triggering a feedback pulse as soon as a heartbeat was detected – in order to suit our experimental protocol to devices that could

<sup>4</sup><http://www.processing.org/>

<sup>5</sup><https://github.com/nutechsoftware/ser2sock>



only average HR over a longer time window (e.g., fitness HR monitor belts). It should be easier to replicate our results without the need to synchronize precisely feedback pulses with actual heartbeats.

The TTS (text-to-speech) system comprised two applications. eSpeak<sup>6</sup> was used to transform textual sentences into phonemes and MBROLA<sup>7</sup> to synthesize phonemes and produce an actual voice. The TTS speed was controlled by eSpeak (120 word per minutes), as well as the pitch (between 65 and 85, values higher than the baseline of 50 to match the teenage appearance of the agents). The four voices (2 male and 2 female, “fr1” to “fr4”) were provided by the MBROLA project. Sentences’ valence did not influence speech synthesis.

## 2.2 Text corpuses

During the first part of the experiment (i.e., the “disruptive” session) sentences were gathered from archives of a french-speaking newspaper. These data were collated by (Bestgen et al., 2004). Sentences were anonymized, e.g., names of personalities were replaced by generic first names. A panel of 10 judges evaluated their emotional valence on a 7-point Likert scale. The final scores were produced by averaging those 10 ratings. We split the sentences in three categories: unpleasant (scores between  $[-3; -1[$ , e.g., a suspect was arrested for murder), neutral (between  $[-1; 1]$ ) and pleasant (between  $]1; 3]$ , e.g., the national sport team won a match) – see section 2.

The sentences of the second part (i.e., the “involving” session) come from the TestAccord Emotion database (Le Tallec et al., 2011). This database originates from a fairy tale for children – see (Wright and McCarthy, 2008) for an example of storytelling as an incentive for empathy. We did not utilize *per se* the associated valences (average of a 5-point Likert scale across 27 judges for each sentence), but as an indicator it did help us to ensure the wide variety of the carried emotions. For instance, deaths or bonding moments are described during the course of the tale.

It is worth noting that when the valence of these corpuses has been established, sentences were presented in their textual form, not through a TTS system.

## 2.3 Procedure

The overall experiment took approximately 50 minutes per subject. 10 French speaking subjects participated in the experiment; 5 males, 5 females, mean

age 30.3 (SD=8.2). The whole procedure comprised the following steps:

1. Subjects were given an informed consent and a demographic questionnaire. While they filled the forms, the equipment was set up. Then we explained to them the procedure of the experiment. We emphasized the importance of the distraction task (i.e., to rate sentences’ valence) and explained to the subjects that we were monitoring their physiological state, without further detail about the exact measures.  $\approx 5$  min.
2. The BVP sensor was placed on the earlobe opposite to the dominant hand, so as not to impede mouse movements. Right after, the headset was positioned. We ensured that subjects felt comfortable, in particular we checked that the headset wasn’t putting pressure on the sensor. We started to acquire BVP data and adjusted the heartbeat detection.  $\approx 2$  min.
3. A training session took place. We started our program with an alternate scenario, adjusting the audio volume to subjects’ taste. Both parts of the experiment occurred, but with only two agents and with a dedicated set of sentences. This way subjects were familiarized with the task and with the agents – i.e., with their general appearance and with the TTS system. During this overview, so as not to bias the experiment, “human” and “medium” conditions were replaced with a “slow” HR feedback (30 BPM) and a “fast” HR feedback (120 BPM). Once subjects reported that they understood the procedure and were ready, we proceeded to the experiment.  $\approx 5$  min.



Figure 5: Our experimental setup. A BVP sensor connects subject’s earlobe to the first laptop, where the human-agent interaction takes place. Subject is wearing a headset to listen to the speech synthesis. A second laptop is used by the experimenter to monitor heartbeats detection.

4. We ran the experiment, as previously described. First the “disruptive” session (80 sentences, 20

<sup>6</sup><http://espeak.sourceforge.net/>

<sup>7</sup><http://tcts.fpms.ac.be/synthesis/mbrola.html>

agents,  $\approx 22$  min), then the “involving” session (138 sentences, 23 agents,  $\approx 17$  min). We were monitoring the data acquired from the BPV sensor and silently adjusted the heartbeat detection through OpenViBE if needed – rarely, a big head movement could slightly move the sensor and modify signal amplitude. Figure 5 illustrates our setup.  $\approx 40$  min.

The newspapers sentences being longer than the ones forming the fairy tale, agents on-screen time varied between both parts. Agents mean display time during the first part was 62.2s, during the second part it was 46.6s.

## 2.4 Measures

We computed a score of social presence for each agent, averaged from the 7-point Likert scales questionnaires presented to the subjects before a new agent were generated. This methodology was validated with spoken dialogue systems by (Möller et al., 2007). This score was composed of 3 items, consistent with ITU guidelines (ITU, 2003). Translated to English, the items were: “Do you consider that the agent is pleasant?” (“very unpleasant” to “very pleasant”); “Do you think it is friendly?” (“not at all” to “very friendly”); “Did it seem ‘alive’?” (“not at all” to “much alive”).

## 2.5 Results

We compared agents’ social presence scores between the “human” and the “medium” conditions for each part. Statistical analyses were performed with R 3.0.1. The different scores were comprised between 0 (negative) and 6 (positive), 3 corresponding to neutral.

A Wilcoxon Signed-rank test showed a significant difference ( $p < 0.05$ ) during the “disruptive” session (means 3.29 vs 2.91) but no significant difference ( $p = 0.77$ ) during the “involving” session (means: 3.30 vs 3.34). H1 is verified while H2 cannot be verified. Besides, when we analyzed further the data, we found no significant effect ( $p = 0.27$ ) of the “human”/“medium” factor on the valence scores attributed to the sentences during the “disruptive” session (means: 3.06 vs 2.91).

Subjects’ HRs were a little higher than expected during the experiment: mean  $\approx 74.73$  BPM (SD = 5.59); to be compared with the average 70 BPM set in the “medium” condition. We used Spearman’s rank correlation test to check whenever this factor could have influenced the results obtained in the “disruptive” session. To do so, we compared subjects’ average HRs with the differences in social presence scores

between “human” and “medium” conditions. There was not significant correlation ( $p = 0.25$ ).

## 3 DISCUSSION

In the course of the “disruptive” session our main hypothesis has been confirmed: users’ engagement toward our HCI increased when agents provided feedback mirroring their physiological state. This result could not be explained by a preference for a certain pace of the HR feedback. For instance, even though their HRs were higher than average, subjects did not prefer agents of the “human” condition because of faster heartbeats. Some of them did possess HRs lower than 70 BPM. The only other explanation lies in the difference of HR synchronization between “human” and “medium” conditions.

Beside agents’ social presence, similarity-attraction effect may influence the general mood of subjects, as they had a slight tendency to overrate sentences valence during “human” condition. It is interesting to note that while the increase in social presence scores is not huge (+13%), it shifts the items from slightly unpleasant to slightly pleasant.

Maybe the effect would have been greater in a less artificial situation. Indeed, despite our experimental protocol, subjects reported afterwards that the TTS system was sometimes hard to comprehend, which bothered them on some occasions. It may have resulted in a task not involving enough for the subjects to really “feel” the emotions carried by the sentences.

Several reasons could explain why the effect appeared only during our “disruptive” session. During the first session agents were displayed on a longer duration (+33%) because of the longer sentences used in the newspapers. The attraction toward a mirrored feedback could take time to occur. In addition, because the task was less disruptive in the second session, subjects were more likely to focus their attention on the content (i.e., the narrative) instead of the interface (i.e., the feedback). This could explain why they were less sensible to ambient cues. Subject were less solicited during the “involving” session; we observed that between agents questionnaires they often removed their hands from the mouse, leaning back on the chair. Lastly, the “involving” session systematically occurred in second position. Maybe the occurrence of the similarity-attraction effect is correlated to the degree of users’ vigilance.

As for subjects’ awareness of the real goal of the study, during informal discussions after the experiments, most of them confirmed that they had no knowledge about the kind of physiological trait the sensor was recording, and none of them realized that at some point they were exposed to their own HR.

This increases the resemblance of our installation with a setup where HR sensing occurs covertly.

## 4 CONCLUSION

We demonstrated how displaying physiological signals close to users could impact positively social presence of embodied agents. This approach of “ambient” feedback is easier to set up and less prone to errors than feedback as explicit as facial expressions. It does not require prior knowledge about users nor complex computations. For practical reasons we limited our study to a virtual agent. We believe the similarity-attraction effect could be even more dramatic with *physically* embodied agents, namely robots. That said, other piece of hardware or components of an HCI could benefit from such approach. While its appearance is not anthropomorphic, the robotic lamp presented by (Gerlinghaus et al., 2012) behaves like a sentient being. Augmenting it with physiological feedback, moreover when correlated to users, is likely to increase its presence.

Further research is of course mandatory to confirm and analyze how the similarity-attraction applies to human-agent interaction and to physiological computing. The kind of feedback given to users need to be studied. Are both audio and visual cues necessary? Does the look of the measured physiological signal need to be obvious or could a heart pulse take the form of a blinking light? In human-human interaction such questions are more and more debated (Slovák et al., 2012);(Walmink et al., 2014). Obviously, one should check that a physiological feedback does not *diminish* user experience. (Lee et al., 2014) suggest it is not the case, but the comparison should be made again with human-agent interaction.

Various parameters in human-agent interaction need to be examined to shape the limits of the similarity-attraction effect: exposure time to agents, nature of the task, involvement of users, and so on. Especially, we suspect the relation between human and agent to be an important factor. Gaming settings are good opportunities to try collaboration or antagonism. Concerning users, some will perceive differently the physiological feedback. As a matter of fact, interoception – the awareness of internal body states – varies from person to person and affects how we feel toward others (Fukushima et al., 2011). It will be beneficial to record finely users reactions, maybe by using the very same physiological sensors (Becker and Prendinger, 2005).

Finally, our findings should be replicated with other hardware. We used lightweight equipment to

monitor HR, yet devices such as the Kinect 2 – if as reliable as BVP or ECG sensors – will enable remote sensing in the near future. But with the spread of devices that sense users’ physiological states, it is essential not to forgo ethics.

Measuring physiological signals such as HR enters the realm of privacy. Notably, physiological sensors can make accessible to others data unknown to self (Fairclough, 2014). Even though among a certain population there is a trend toward the exposition of private data, if no agreement is provided it is difficult to avoid a violation of intimacy. Users may feel the urge to publish online the performances associated to their last run – including HR, as more and more products that monitor it for fitness’ sake are sold – but experimenters and developers have to remain cautious.

Physiological sensors are becoming cheaper and smaller, and hardware manufacturers are increasingly interested in embedding them in their products. With sensors acceptance, smartwatches may tomorrow provide a wide range of continuous physiological data, along with remote sensing through cameras. If users’ rights and privacy are protected, this could provide a wide range of areas for investigating and putting into practice the similarity-attraction effect. Heart rate, galvanic skin response, breathing, eye blinks: we “classify” events coming from the outside world and it influences our physiology. An agent that seamlessly reacts like us, based on the outputs we produce ourselves, could drive users’ engagement.

## REFERENCES

- Agelink, M. W., Malessa, R., Baumann, B., Majewski, T., Akila, F., Zeit, T., and Ziegler, D. (2001). Standardized tests of heart rate variability: normal ranges obtained from 309 healthy humans, and effects of age, gender, and heart rate. *Clinical Autonomic Research*, 11(2):99–108.
- Becker, C. and Prendinger, H. (2005). Evaluating affective feedback of the 3D agent max in a competitive cards game. In *Affective Computing and Intelligent Interaction*, pages 466–473.
- Berta, R., Bellotti, F., De Gloria, A., Pranatha, D., and Schatten, C. (2013). Electroencephalogram and Physiological Signal Analysis for Assessing Flow in Games. *IEEE Transactions on Computational Intelligence and AI in Games*, 5(2):164–175.
- Bestgen, Y., Fairon, C., and Kerves, L. (2004). Un barometre affectif effectif: Corpus de référence et méthode pour déterminer la valence affective de phrases. *Journées internationales d’analyse statistique des données textuelles (JADT)*.
- Fairclough, S. H. (2014). Human Sensors - Perspectives on the Digital Self. Keynote at Sensornet ’14.



- Fukushima, H., Terasawa, Y., and Umeda, S. (2011). Association between interoception and empathy: evidence from heartbeat-evoked brain potential. *International journal of psychophysiology: official journal of the International Organization of Psychophysiology*, 79(2):259–65.
- Gerlinghaus, F., Pierce, B., Metzler, T., Jowers, I., Shea, K., and Cheng, G. (2012). Design and emotional expressiveness of Gertie (An open hardware robotic desk lamp). *IEEE RO-MAN '12*, pages 1129–1134.
- Harrison, C., Horstman, J., Hsieh, G., and Hudson, S. (2012). Unlocking the expressivity of point lights. In *CHI '12*, page 1683, New York, New York, USA. ACM Press.
- Huppi, B. Q., Stringer, C. J., Bell, J., and Capener, C. J. (2003). United States Patent 6658577: Breathing status LED indicator.
- ITU (2003). P. 851, Subjective Quality Evaluation of Telephone Services Based on Spoken Dialogue Systems. *International Telecommunication Union, Geneva*.
- Karlesky, M. and Isbister, K. (2014). Designing for the Physical Margins of Digital Workspaces: Fidget Widgets in Support of Productivity and Creativity. In *TEI '14*.
- Kranjec, J., Beguš, S., Geršak, G., and Drnovšek, J. (2014). Non-contact heart rate and heart rate variability measurements: A review. *Biomedical Signal Processing and Control*, 13:102–112.
- Le Tallec, M., Antoine, J.-Y., Villaneau, J., and Duhaut, D. (2011). Affective interaction with a companion robot for hospitalized children: a linguistically based model for emotion detection. In *5th Language and Technology Conference (LTC'2011)*.
- Lee, K. M. and Nass, C. (2003). Designing social presence of social actors in human computer interaction. In *Proceedings of the conference on Human factors in computing systems - CHI '03*, number 5, page 289, New York, New York, USA. ACM Press.
- Lee, M., Kim, K., Rho, H., and Kim, S. J. (2014). Empa talk. In *CHI EA '14*, pages 1897–1902, New York, New York, USA. ACM Press.
- Lisetti, C. L. t. and Nasoz, F. (2004). Using Noninvasive Wearable Computers to Recognize Human Emotions from Physiological Signals. *EURASIP J ADV SIG PR*, 2004(11):1672–1687.
- MacDorman, K. (2005). Androids as an experimental apparatus: Why is there an uncanny valley and can we exploit it. *CogSci-2005 workshop: toward social mechanisms of android science*, 3.
- Mandryk, R., Inkpen, K., and Calvert, T. (2006). Using psychophysiological techniques to measure user experience with entertainment technologies. *Behaviour & Information Technology*.
- Matthews, G., Campbell, S. E., Falconer, S., Joyner, L. a., Huggins, J., Gilliland, K., Grier, R., and Warm, J. S. (2002). Fundamental dimensions of subjective state in performance settings: Task engagement, distress, and worry. *Emotion*, 2(4):315–340.
- Möller, S., Smeele, P., Boland, H., and Krebber, J. (2007). Evaluating spoken dialogue systems according to de-facto standards: A case study. *Computer Speech & Language*, 21(1):26–53.
- Picard, R. W. (1995). Affective computing. Technical Report 321, MIT Media Laboratory.
- Prendinger, H., Dohi, H., and Wang, H. (2004). Empathic embodied interfaces: Addressing users' affective state. In *Affective Dialogue Systems*, pages 53–64.
- Reidsma, D., Nijholt, A., Tschacher, W., and Ramseyer, F. (2010). Measuring Multimodal Synchrony for Human-Computer Interaction. In *2010 International Conference on Cyberworlds*, pages 67–71. IEEE.
- Renard, Y., Lotte, F., Gibert, G., Congedo, M., Maby, E., Delannoy, V., Bertrand, O., and Lécuyer, A. (2010). OpenViBE: An Open-Source Software Platform to Design, Test, and Use Brain-Computer Interfaces in Real and Virtual Environments. *Presence: Teleoperators and Virtual Environments*, 19(1):35–53.
- Slovák, P., Janssen, J., and Fitzpatrick, G. (2012). Understanding heart rate sharing: towards unpacking physiosocial space. *CHI '12*, pages 859–868.
- Walmink, W., Wilde, D., and Mueller, F. F. (2014). Displaying Heart Rate Data on a Bicycle Helmet to Support Social Exertion Experiences. In *TEI '14*.
- Winton, W. M., Putnam, L. E., and Krauss, R. M. (1984). Facial and autonomic manifestations of the dimensional structure of emotion. *Journal of Experimental Social Psychology*, 20(3):195–216.
- Wright, P. and McCarthy, J. (2008). Empathy and experience in HCI. *CHI '08*.