Matching artificial agents' and users' personalities: designing agents with regulatory-focus and testing the regulatory fit effect

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Abstract

Artificial agents are becoming more than human-computer interfaces: they are becoming artificial companions, interacting on a long-term basis and building a relationship with the user. This evolution brought new challenges, such as designing agents with personalities to the benefits of users. We endow artificial agents with regulatory focus, taking a socio-cognitive approach of personality, by using machine-learning techniques. We test whether this personality can be perceived by users and if there is a regulatory fit effect on the users credibility judgement of the agent (i.e. is the agent perceived as more credible if its regulatory focus is the same as that of the user?). Our results show agents regulatory focus can be adequatly perceived by users playing a board game against an agent expressing its regulatory focus via machine-learned strategies. A regulatory fit effect was found on the likeability judgment for prevention focus users but not for promotion focus users.

Keywords: Artificial agents; Personality; Regulatory fit; User study; Affective computing

Introduction

In the last decade, software agents were brought to a new level, due to technological evolutions : artificial agents ceased to be only human-computer interfaces to become artificial companions (Benyon & Mival, 2010). An articial companion can be defined as "a personalised, multi-modal, helpful, collaborative, conversational, learning, social, emotional, cognitive and persistent computer agent that knows its owner, interacts with the user over a long period of time and builds a (long-term) relationship to the user" (Sviatlana, Busemann, & Schommer, 2012). If we are going to be in "relationship" with our artificial companions, we better be compatible ! But compatibility is not just a concept created by dating websites. There is a wide range of studies about the impact of personality on any kind of relationships: from couples (Robins, Caspi, & Moffitt, 2000) to teachers (Karwowski, 2011) or work teams (Nahrgang, Morgeson, & Ilies, 2009). Thus, it seems logical to think that endowing an artificial companion with personality could have benefits.

Personality can be define as a coherent patterning of affect, behavior, cognition, and desires (goals) over time and space (Revelle & Scherer, 2009). From an affective computing perspective, believability is assessed by the consistency and the coherence of an artificial entity at various levels (psychological and physical; intrapersonal as well as social) (Isbister & Doyle, 2002; Niewiadomski, Demeure, & Pelachaud, 2010). Thus, endowing artificial companions with personality could also help to increase the companion's believabiity, hence easing the interaction and thereby, producing an adequate environment for a relationship to take place. At the same time, personality complementarity and similarity have been shown as important factors for the acceptance of an interface by a user (Nass & Lee, 2001). So, if something can be build between one user and its artificial companion, both personalities (user's and companion's) will impact this relationship.

In this article, we propose to take a socio-cognitive approach of personality and use the regulatory focus theory (Higgins, 1997) as a framework to endow artificial agents with personality. Regulatory focus theory comes with the concept of regulatory fit (Higgins, 2005): when people perceived a "fit", i.e. congruent regulatory focus, between them and an object (in every sense), they feel "right" about their interaction and the experience of "correctness and importance" is passed on the object, increasing its superficial worth (Avnet & Higgins, 2003). We will adress three questions: 1/ how can we implement regulatory focus for artificial agents, 2/ is the intended personality perceived as such, and 3/ can we reproduce a regulatory fit effect between such an agent and users? Therefore, we will present our data-driven approach of personality modelisation, along with an user study adressing the last two issues.

Theorical Background

Personality and affective computing

In 2000, Nass and Moon (Nass & Moon, 2000) suggest the Computers As Social Actors (CASA) paradigm. The CASA paradigm states that people tend to adopt social attitudes with machines that can elicit social heuristics. So, personality can be attributed by users to a computer and have an influence over users' behaviors. In this view, designing specific personalities that are perceived such as they were designed seems especially important. If computer scientists make sometimes their own model of personality (Gmytrasiewicz & Lisetti, 2002), most of the works in affective computing lean on psychological models. As the Five Factors Model (FFM) (Costa & McCrae, 1992) is a dominant and well-known model in personality psychology, this model is naturally becoming the most used reference in affective computing. The five dimensions proposed, also known as the Big Five, are : Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism. The concept of trait can easily be approached in a numerical way, an ideal way for computer scientists. The five traits are used, all or in subsets, as variables altering behaviors of artificial agents (for a state-of-the-art, see (Vinciarelli & Mohammadi, 2014)). Regarding users' preferences in terms of artificial personalities, compatibility of personalities have been studied inside the same FFM framework. For now, researchers focuses especially on the Extraversion trait (because extraversion is the most "conveyable" trait through verbal and non-verbal behaviors). If we overlook this limitation, literature shows that similarity attraction is found (e.g. an introverted person prefers a introverted entity) (Nakajima et al., 2003) as well as complementary attraction (e.g. an introverted person prefers an extraverted entity) (Tapus, Tapus, & Matari, 2008). This effect may be moderated by the social role of the artificial entity and the stereotype expectations associated with this role (Joosse, Lohse, Perez, & Evers, 2013; Tay, Jung, & Park, 2014). That is one of the limits of the traits approach. Traits theories are especially useful for the description of the personality. But, by looking at the global structure of personality, they hide intraindividual differences.

On the contrary, socio-cognitive models are explicative per se. The *socio-cognitive approach to personality* underlines the importance of a situation in exhibiting personality behaviors (Bandura, 1999). This approach attempts to understand cognitive and social processes that lead to personality. For that purpose, it focuses on the interaction between the person and the social context and highlights the intra-individual differences (Mischel, Shoda, & Smith, 2004). That's why we take a more socio-cognitive approach of personality (Faur, Clavel, Pesty, & Martin, 2013). Further to our previous work, we propose to use the regulatory-focus theory (Higgins, 1997) as a framework for endowing artificial agents with personality.

Using the regulatory focus theory

The regulatory-focus theory (Higgins, 1997) distinguishes between two self-regulation strategies: promotion-focus, which look into the presence or absence of positive outcomes, gains versus nongains and prevention-focus, which look into the presence or absence of negative outcomes, losses versus non-losses. Promotion-focus people would be more prone to using their ideal-selves as guides for their behaviors (i.e., they are looking for being what they want to be) than prevention-focus people, who would prefer using ought-selves (i.e., they are looking for being what they think they have to be). Promotion and prevention are two independent dimensions. One person has both a promotion-focus and a prevention-focus score. Regulatory focus can be situational, i.e. induced by the context, but theory states that people have a chronic focus, i.e. an "habitual" focus used by default. The orientation of this chronic focus is equivalent to the highest of both promotion-focus score and prevention-focus score. The regulatory focus theory also proposes the concept of regulatory-fit.

Regulatory-fit states that matching user's regulatory-focus and means used to approach one goal creates a feeling of rightness about the pursued goal and increases task engagement (Higgins, 2005). For example, a user in a state of promotion-focus will be more receptive to promotion-oriented messages (and respectively for prevention-focus) (Lee & Aaker, 2004). Benefits of regulatory fit are explored in several domains like in working environments (Park, Hinsz, & Nickell, 2015) or communications (Ludolph & Schulz, 2015) but not in affective computing. Yet, if an artificial companion can create a state of regulatory-fit with its user, we can hope that the feeling of rightness and correctness will be transferred to the agent, increasing its likeability/credibility (i.e. its capacity of being perceived as believable and convincing (Burgoon et al., 2000)) along with the user's engagement towards the agent and the task they are doing together.

To our knowledge, there is currently no study exploring users' preferences for artificial personalities based on the regulatory fit or the regulatory focus theory.

Methodology

Convey personality via game strategies

In this paper, we used a board game strategy as the first and only modality for expressing the artificial agents personality. Several links have been made between personality and games, in psychology (Bartle, 1996) and in computer sciences (Johansson & Verhagen, 2014). Games are quite relevant for designing and evaluating affective agents (Gratch, Marsella, Wang, & Stankovic, 2009; Courgeon, Clavel, & Martin, 2014). We selected as an application a board game, named Cant Stop (designed by Sid Sackson). This game belongs to the type stop-or-again. It is a game asking to choose between either stopping a turn, i.e. saving the current gains but loosing in speed or playing again, i.e. taking the risk of loosing the current gains to win more. We selected this very game because it enables to study strategies in terms of promotion and prevention since at each turn the player has to 1/ select a movement that can be more or less risky and 2/ make a choice between a vigilant strategy (stopping) or an eager strategy (playing again).

Data-driven implementation

We propose to use a data-driven implementation. By using machine learning and classification methods, we propose to test whether people can perceive the intended regulatory-focus of an artificial agent exhibiting a strategy learned from human data. The results about the perception of regulatory-focus could validate the concept as useful to convey personality and also guide future implementations if the classification models used are interpretable. The description of the data-driven implementation is beyond the scope of this paper. To put it in a nutshell, fifteen participants (13 men, 2 women ; age M = 29,7 years, SD = 10,2) played against each other Cant Stop games. Prior to the study, each participant had answered the Regulatory Focus Questionnaire Proverbs Form (RFQ-PF), a French questionnaire measuring the strengh of the two self-regulatory strategies. Participants played via computers, where all the games where logged, in order to be analyzed later. Then, we proceed to classification with features calculated according to our own analyse of the game with the sofware Weka (version 3.7). We computed three models : one for the choice of a move during the game and two for the "stop-or-again" decision (with and without taking into account personality scores as a feature; the latter should smooth interindividual differences to produce a "depersonalized" strategy). We choose to use the Alternative Decision Tree classifier (ADTree) (Holmes, Pfahringer, Kirkby, Frank, & Hall, 2002) because of differents advantages : the robustness, the interpretability of the tree and the ease of implementation. We performed a 10-fold stratified cross-validation on the models produced and benchmarked the results against different classifiers which finally presented equivalent or lesser performances (e.g. results for our "stop-or-again" decision model with personality: Incorrectly categorized items = 19.7%; Kappa statistic = 0.33; Receiver operating characteristic (ROC) area = 0.80). We directly implemented the decision trees as decision-making strategies for the agents.

Experimental design

In order to test the users' perception of agents' personality and the regulatory fit effect, we wanted a (scientifically speaking) control agent: an agent playing without personality. In psychology, there is no such thing as a person with no personality. So what could it be in affective computing? Two types of strategies are generally used as control in the domain: random strategy (but does the absence of planned consistency convey an absence of personality?) or "traditional AI" strategy (but does the absence of implemented personality is equivalent to the absence of personality?). Finally, we considered to have 4 types of agent : 1/ the random agent (Rand), which chooses randomly its moves and has a 50% probability to stop its turn ; 2/ the "average" agent (Avg), which follows the "depersonalized" strategy ; 3/ the promotion agent (RF-Pro), which has a promotion score of 7 and a prevention score of 1 ; 4/ the prevention agent (RF-Pre), which has a promotion score of 1 and a prevention score of 7. The so-called RF-agents follow the same decision tree, where some branches are conditionned by the value of personality scores. Concerning users, we did not select them by testing their chronic regulatory-focus before the study. At the end, we had 14 participants with a chronic promotion focus and 6 with a chronic prevention focus.

User study

Hypothesis

We make 3 hypothesis concerning the results of this study:

- H1: The differences in agents personalities are perceived by the human player
- H2: The credibility of the agent is increased by the presence of personality. The RF-agents are perceived as more likeable and more intelligent than the Rand-agent and the Avg-agent.
- H3: According to the regulatory-fit theory, human player oriented as promotion find RF-Pro agent more credible than other agents (respectively for RF-Pre).

Design

Prior to the study, each subject had answered the Regulatory Focus Questionnaire Proverbs Form (RFQ-PF), a French questionnaire measuring the chronic regulatory-focus with 18 questions to answer on a 7-point Likert scale. During the study, the following procedure was applied. First, the participant is explained the rules of Cant Stop by viewing a explicative video. During the tutorial video, the possibility is given to the participant to pause the video and to replay if necessary. Second, the participant plays a tutorial game against the computer in order to familiarize with the game itself and its interface. The participant is informed that the computer will make random choices during the tutorial game. The experimenter answers questions if some of the rules remain unclear. Third, the participant is informed that he or she will play 4 games against different artificial agents. The participant is also informed that he or she will have to evaluate the agents personality after each game. There is no visual display of the artificial agent, the only modality for evaluate the agents personality is the way the agent plays the game. The different conditions are counterbalanced to compensate a potential effect of order. After each game against an agent, the participant answers the RFQ-PF in an other-ratings form (i.e. to caracterize the agents strategies during the game), along with 10 questions from the Godspeed Questionnaire (Bartneck, Kuli, Croft, & Zoghbi, 2009) (5 about likeability and 5 about the perceived intelligence of the agent ; 5-point Likert scale) as a credibility measure.

Participants

Twenty participants took part in this evaluation study. There were 11 men and 9 women (age M = 30.6 years, SD = 8.1). Of the participants, 17 were native french speakers and 3 were bilingual.

Results[1]

First, we look at the mean and standard deviation for each measure. We also computed the coefficient of quartile variation (CQV ; $(Q3-Q1)/(Q1+Q3)$), which offers a comparable statistic of dispersion (Bonett, 2006) and the Finn coefficient[2], as an index of the interraters agreement (Finn, 1970). Complete results are presented in Table 1. To summarize, important results are:

[1] Data were analysed using R, version 3.1.2, http://www.R-project.org

[2] R package *irr*, version 0.84

- Dispersion of data: The CQV of the Rand agent for personality scores is, on average, 1.5 times higher than other agents CQV.

- Interraters agreement: Finn coefficient of the Rand agent are the lowest for the promotion score and the prevention score.

- Personality scores:
  - Promotion score: the RF-Pro agent and the Avg-agent are rated high (resp. M=5.26 ; SD=1.28 and M=5.30 ; SD=1.44) unlike the RF-Pre agent and the Rand-agent (resp. M=3.09 ; SD=1.22 and M=3.53 ; SD=1.47).
  - Prevention score: the RF-Pre agent and the Rand-agent are rated high (resp. M=5.58 ; SD=0.73 and M=4.51 ; SD=1,71) unlike the RF-Pro agent and the Avg-agent (resp. M=2.91 ; SD=1.33 and M=3.18 ; SD=1.40).

- Credibility scores:
  - Likeability: scores are around 3 (on a 5-point scale) for all the agents.
  - Perceived intelligence: scores have an higher range : from 2.63 (Rand-agent) to 3.85 (RF-Pre agent).

For the analysis of differences between conditions, we applied non-parametric statistics, as the assumption of normality could not be granted in these conditions. We used the Friedman test as principal analysis and pairwise comparisons using Wilcoxon signed rank test as post-hoc test. For the post-hoc tests, p-values were adjusted using the Holm correction. Friedman tests reported significant differences for promotion-score ($\chi^2(3) = 23.44; p < 0.001$), prevention-

Table 1: Descriptive statistics of the different scores collected during the study ; *Pro Sc. = promotion score ; Pre Sc. = prevention score ; Lik. = likeability ; Perc. Int. = perceived intelligence ; CQV = Coefficient of Quartile Variation*

		Rand	**Avg**	**RF-Pro**	**RF-Pre**
Pro Sc.	Mean	3.53	5.3	5.26	3.09
	SD	1.47	1.44	1.28	1.22
	CQV	32%	15%	14%	20%
	Finn coeff.	0.46	0.48	0.59	0.63
Pre Sc.	Mean	4.51	3.18	2.91	5.58
	SD	1.71	1.4	1.33	0.73
	CQV	30%	37%	25%	8%
	Finn coeff.	0.27	0.51	0.56	0.87
Lik.	Mean	3.3	3.22	3.02	3.51
	SD	0.78	0.67	0.95	0.75
	CQV	19%	13%	18%	14%
Perc. Int.	Mean	2.63	2.94	3.11	3.85
	SD	0.6	1.16	0.98	0.68
	CQV	18%	33%	27%	11%

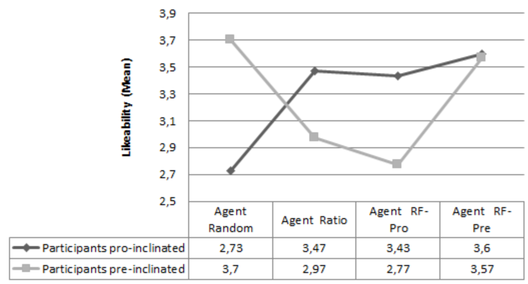

Figure 1: Interaction between the participant's personality and the agent's personality regarding the likeability of the agent.

score ($\chi^2(3) = 23.28; p < 0.001$) and the perceived intelligence ($\chi^2(3) = 15.18; p = 0.002$). We do not found significative differences for the likeability ($\chi^2(3) = 2.24; n.s.$). Post-hoc tests show the following results:

- Promotion scores: the RF-Pro agent is significatively rated higher than the RF-Pre agent ($p \leq 0.001$) and the Rand-agent ($p \leq 0.01$). There is no significative difference between the RF-Pro agent and the Avg-agent.

- Prevention scores: the RF-Pre agent is significatively rated higher than the RF-Pro agent ($p \leq 0.001$) and the Avg-agent ($p \leq 0.01$). There is no significative difference between the RF-Pre agent and the Rand-agent.

- Perceived intelligence: the RF-Pre agent is rated significatively higher than the Rand-agent, the Avg-agent and the RF-Pro agent (resp. $p \leq 0.01; p \leq 0.05; p \leq 0.05$). There is no significative difference between the three other agents.

For the analysis of interactions, we choose to compare only participants with the strongest chronic focus (i.e. highest differences between promotion-focus and prevention-focus scores) as they are the more proned to show a regulatory-fit effect. We selected a subset of data with the six more promotion-inclinated and the six more prevention-inclinated participants. We performed an adjusted rank transfom test (Leys & Schumann, 2010), which is a robust way of testing interactions on non-parametric data. We found a significative interaction between the regulatory-focus inclination of the participant and the type of agent for the likeability ($F(3,30) = 4.532; p < 0.01$; partial η^2=0.31). As shown in Figure 1, prevention-oriented participants have found the Rand and the RF-Pre agents (which have been both perceived as prevention-focus) more likeable thant the Avg and the RF-Pro agents (which have been both perceived as promotion-focus). Promotion-oriented participants have found the Rand agent less likeable than any other agent. No other significative interaction was found.

Discussion & perspectives

We first asked if users can perceive the differences between agents' personalities (H1). This first hypothesis is almost validated. On the one hand, results show that our RF-Pro and RF-Pre agents has been respectively perceived as promotion-oriented and prevention-oriented, as we expected. We could say that our data-driven strategies successfully convey the agent's regulatory-focus. On the other hand, our Rand and Avg agents have been respectively perceived as prevention-oriented and promotion-oriented. This result points out the difficulty of controlling personality perception of virtual agents. We raised our concerns (cf. Methodology - Experimental design) and, as brought up by (Liu, Tolins, Tree, Walker, & Neff, 2013), by assessing personality with questionnaires, participants may be driven to rate something they had not perceived. Besides, such attribution could also be explain by what Shermer (Shermer, 2012) called patternicity and agenticity : respectively "the tendency to find meaningful patterns in meaningless noise" and "the tendency to infuse [these] patterns with meaning, intention and agency". Otherwise, we have taken an user-centered and data-driven approach with interpretable outputs. Because these outputs can convey regulatory-focus, they could also inform us on a psychological side, on the links between human regulatory-focus and risk-taking in a stop-or-again game. On the computing side, such data and performances could fed symbolical and theory-driven models, which suppose more assumptions about cognitive processes. This complementary approach could gives us more insights in the possible internal mechanisms to endow virtual agents with regulatory-focus.

Concerning the credibility of the different agents (H2), the hypothesis is partially validated. We found a difference in favor of the RF-Pre agent regarding the perceived intelligence. The RF-Pro agent was rated as more intelligent than the Rand and Avg agents but the difference was not significative. Considering our number of subjects, we could not say if the non-significativity is due to a lack of data or to a real difference due to the agent's strategy. Nevertheless, we found no differences in likeability. Participants orally reported difficulties to evaluate likeability, because they found that the interaction was not sufficient to judge on the agents sympathy. This result also raised a fundamental question: how are we measuring such a concept?

Our third hypothesis, observing an effect of regulatory fit between the user's and the agent's chronic regulatory focus (H3) is also partially validated. We found an interaction between the user's focus and the type of agent regarding the likeability score: prevention-oriented users found the RF-Pre agent and the Rand agent more likeable than the RF-Pro agent and the Avg agent. Because RF-Pre and Rand agents were both perceived as prevention-oriented, we could say that regulatory fit happened for prevention-focus users. We did not find such effect for promotion-focus users. This result raised an other question: should we focus on the user's perception of the personality we tried to convey or only on the effect of the agent perceived personality (whatever it is) on the user?

To conclude, we have shown that it is possible to successfully endow artificial agents with regulatory-focus and that this regulatory-focus can be accuretly perceived by users. We also provided data which point to the possibility of using the concept of regulatory fit with artificial agents. As perspectives, we list directions for future works in order to try to provide data for answering the questions raised by our results and better understand the regulatory fit effect with artificial agents : making more longitudinal studies because only repeated interactions could allow users to form a real model of the agent's personality; using multi-modality to enhance the interaction, such as verbal and non-verbal behaviors during the game by providing a physical representation of a virtual agent; complementing self-report measures by users' behaviors measures, such as engagement for example.

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